Report to the Dirigo Health Agency

Dirigo Health Reform Act:
Aggregate Measurable Cost Savings (AMCS) for Year 4

November 3, 2009

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1. EXECUTIVE SUMMARY

YEAR 4 AGGREGATE MEASURABLE COST SAVINGS (AMCS)

The Year 4 AMCS for the Dirigo Health Agency (the Agency) has been developed by **s**chramm▫**r**aleigh **H**EALTH **S**TRATEGY (**srHS**) and Dr. Adam Atherly of the University of Colorado. In developing AMCS we reviewed multiple sources on information, including the Dirigo Health Reform Act of 2003, as amended, and prior years' determinations of AMCS. We have included in this report only initiatives supportable by available data and methodologies. These initiatives are:

A. Bad Debt and Charity Care (BD/CC) reflecting *Uninsured and Underinsured Initiatives:* calculates the reduction or avoidance of BD/CC due to Dirigo by comparing the percentage of those without insurance under two scenarios – in the absence of Dirigo and in the presence of Dirigo. BD/CC is also known as uncompensated care and are the expenditures incurred by hospitals and other providers when people can't or don't pay their medical bills.

B. Cost per Case-Mix Adjusted Discharge (CMAD) reflecting *Hospital Savings Initiatives:* compares hospital costs under two scenarios – in the absence of Dirigo and in the presence of Dirigo. The CMAD measures hospital costs on a per case-mix adjusted discharge basis, which allows for comparison across hospitals because it is adjusted for the varying severity of discharges.

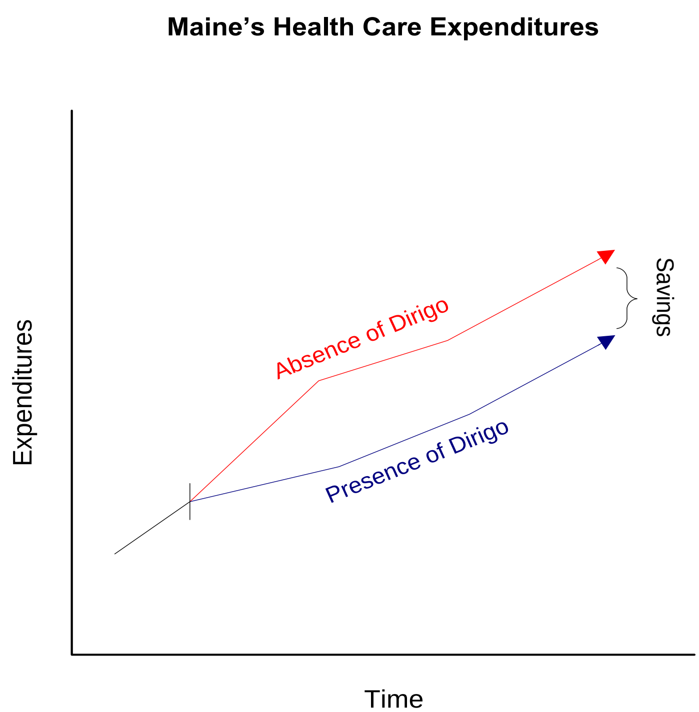
C. Overlap: Overlap measures any savings that may be duplicative among the above calculations in order to remove any overstatement of savings (previously referred to as double-counting) or understatement of savings (previously referred to as under-counting) between them.

The process established during Year 1 of the AMCS proceedings, and followed through to this year, continues to recognize that while we are measuring the impact of Dirigo for the fourth year (Year 4), the actual initiatives and their resulting impacts cover differing annual time periods as a result of differing implementation dates associated with Dirigo. Therefore, for this year's AMCS:

- the BD/CC measurement addresses the impact on BD/CC expenditures for Maine health care providers during calendar year 2008 (CY2008), that is, January 1, 2008 to December 31, 2008, and
- the CMAD measurement addresses the impact on CMAD expenditures for Maine hospitals during state fiscal year 2007 (SFY2007), that is, July 1, 2006 to June 30, 2007.

The AMCS calculations measure the change in certain Maine health care expenditures in the presence of the Dirigo reforms compared to an estimate of what costs in Maine would have been in the absence of Dirigo. Our estimates are based on econometric regression models which measure the effect of the Dirigo reforms on health care expenditures in Maine compared to several control groups, including both Maine's pre-Dirigo experience and trends in other states, plus changes in other factors that may be associated with changes in expenditures. If expenditures in the absence of Dirigo are greater than those in the presence of Dirigo, the difference between these scenarios is aggregate measurable cost savings attributable to Dirigo (see Figure 1).

Figure 1: AMCS as Difference between Dirigo-Absence and Dirigo-Presence Scenarios



In simplest terms, once the various calculations occur, the Year 4 AMCS is equal to A+B-C (using the lettered calculations on page 1). These calculations result in the following total AMCS for Year 4:

Figure 2: Year 4 AMCS Sum Total

Initiative	Calculation	Year 4 Amount
A – Uninsured and Underinsured Initiatives	BD/CC – CY2008	$11.6 million
B – Hospital Savings Initiatives	CMAD – SFY2007	$67.3 million
C – Overlap	Overlap	$0.0 million
Year 4 AMCS = A+B-C		$78.9 million

On the next three pages, summary abstracts are provided that briefly describe the methods that result in the three AMCS amounts above. Following that, we have separate report sections for each of the three AMCS amounts above to provide detailed information about their corresponding data, methodology, and results. Please note that a list of abbreviations and acronyms used in this report are summarized in Appendix A.

ABSTRACT: AMCS DUE TO REDUCTIONS IN BAD DEBT AND CHARITY CARE (BD/CC)

Abstract

Background: Dirigo included a number of initiatives that were intended to reduce the amount of bad debt and charity care provided by Maine health care providers. The purpose of this analysis is to estimate the relationship between the Dirigo health reform and the amount of bad debt and charity care (BD/CC) provided by Maine health care providers.

Methods: The BD/CC calculation is completed in two steps. The first step used a logit regression model with state level fixed effects to capture the time-invariant differences among states. Data was primarily derived from the Current Population Survey (CPS). The second step used a published figure on uncompensated care costs per capita trended by National Health Expenditures (NHE) data to estimate the cost of uncompensated care in Maine in calendar year 2008. The results of the two steps were multiplied to develop the total cost of care that would have been uncompensated in the absence of Dirigo in calendar year 2008.

Results: Controlling for other factors, Dirigo lowered the rate of uninsurance in Maine by 1.94% in adults between the ages of 19 and 64 who are not eligible for the State Children's Health Insurance Program (SCHIP) or Medicaid (or age eligible for Medicare). This difference is statistically significant, with a z statistic of -3.63 and a p value of less than 0.0001. The "Dirigo Effect" shows the "difference-in-differences" – that is, differential changes in the difference between Maine and the rest of the country during the Dirigo years.

Conclusion: Since the enactment of the Dirigo Health Reform Act, there has been a reduction in the rate of uninsurance among the non-elderly in Maine when compared to changes in national rates of uninsurance. Had Dirigo not been enacted, an additional 13,015 non-elderly Maine residents would have lacked health coverage in 2008. Thus, the Dirigo initiative significantly reduced the rate of uninsurance in for individuals not eligible for Medicaid, SCHIP, or Medicare. The mean per capita cost for an uninsured person for BD/CC is estimated to be $893 in 2008. This results in an estimate that decreases in uninsurance prevalence due to the Dirigo Act yielded cost savings in 2008 of $11.6 million uncompensated care. This does not include the additional savings due to increased service utilization by the previously uninsured since data necessary for the calculation was not available.

ABSTRACT: AMCS DUE TO REDUCTIONS IN COST PER CASE-MIX ADJUSTED DISCHARGE (CMAD)

Abstract

Background: Dirigo, in an attempt to rein in health care costs, included voluntary targets for Maine's hospitals to limit their cost per case-mix adjusted discharge (CMAD) increase on an annual basis. The purpose of this analysis is to estimate the relationship between the Dirigo health reform and the average cost per hospitalization in Maine.

Methods: In this analysis, we employed a fixed effects model using the natural log of CMAD as the dependent variable. Data was primarily derived from the publicly available Medicare Cost Reports (MCRs) downloaded from the Centers for Medicare and Medicaid Services (CMS) website. Variables from published studies were reviewed to determine the specifications for the model. The analysis was completed for the time period July 1, 2006 to June 30, 2007 (SFY2007). We also present results using different model specifications and with CMAD (unlogged) as the dependent variable. The results are robust to the various specifications.

Results: This analysis finds that Dirigo had a statistically significant effect on average CMAD costs, with a t statistic of -2.00 and a p value of 0.046. This suggests that Dirigo reduced CMAD costs by 3.6%. In SFY2007, that difference was $220 per hospitalization in Maine ($6,102 actual versus $6,322 projected without Dirigo).

Conclusion: The analysis shows that without Dirigo, CMAD costs in Maine would be higher than it is with Dirigo. To determine overall savings to the Maine health care system, the reduction in CMAD costs must be applied to the appropriate discharge figure for SFY2007. There were a total of 380,435 case-mix adjusted inpatient and outpatient equivalent discharges in SFY2007. Reducing this figure for those discharges associated with cost-based reimbursement results in an adjusted total volume of 306,089 for SFY2007. The total CMAD savings associated with Dirigo for SFY2007 is equal to 306,089*$220 = $67.3 million.

ABSTRACT: AMCS ADJUSTMENT DUE TO OVERLAP IN BD/CC AND CMAD

Abstract

Background: Dirigo included numerous initiatives intended to rein in the rate of growth of health care expenditures in Maine. At least two of those initiatives, reductions in the amount of bad debt and charity care (BD/CC) due to reductions in Maine's uninsurance rate and voluntary limits on hospital costs per case-mix adjusted discharge (CMAD) increases on an annual basis have had a measurable impact reducing the rate of growth in health care costs in Maine. The purpose of this analysis is to determine if the savings methodologies for BD/CC and CMAD could potentially overlap, resulting in the savings estimates being overstated or understated.

Methods: The analysis focused on deconstructing the CMAD initiative to determine which of its elements were impacted by the BD/CC savings initiative.

Results: The analysis found that there are potential overlaps between the BD/CC savings and the CMAD savings. An understatement of CMAD savings could result equally from Dirigo reducing the uninsured rate and increasing allowable costs on MCRs as well as lowered pressure on cost reductions due to insurance reimbursement for existing utilization that previously was uncompensated care. However, there is not sufficient data available to determine a calculable understatement of savings due to these overlaps. There may be an effect on savings due to an increase in CMAD volume caused by new utilization of services by the previously uninsured identified in the BD/CC analysis, however this could result in an understatement or overstatement of savings.

Conclusion: There are potential overlaps between the BD/CC and CMAD savings initiatives. Careful examination shows that the BD/CC methodology has the potential to both overstate savings and understate savings for CMAD. As the net impact is indeterminate, the net calculable overlap is zero.

2. YEAR 4 AMCS CALCULATIONS – BD/CC

In 2003, the State of Maine enacted the Dirigo Health Reform Act (Dirigo), the first in a series of comprehensive statewide health system reforms designed to reduce cost and improve quality and access to health care statewide. This section of the report focuses on Dirigo's effect on the amount of bad debt and charity care (BD/CC) provided to the uninsured in Maine. The calculation is a two-step process. In the first step, we rely primarily on the Current Population Survey (CPS) to estimate the effect of Dirigo on the number of uninsured and in the second step; we use a published figure on uncompensated care costs per capita trended by National Health Expenditures (NHE) data to estimate the cost of uncompensated care in Maine in calendar year 2008. We then multiply the results of the two steps to develop the total cost of care that would have been uncompensated in the absence of Dirigo in calendar year 2008.

This evaluation examines the following questions:

1. Is there a statistically significant relationship between the implementation of Dirigo and the number of uninsured in Maine?
2. If so, is the relationship positive or negative? A positive relationship would indicate that Dirigo had increased the number of uninsured in Maine and a negative relationship would indicate that Dirigo had reduced the number of uninsured in Maine.
3. What is the statistical strength of the relationship?

If the relationship is negative, we then draw on published estimates of the effect of the uninsured on the amount of bad debt and charity care (BD/CC) provided per uninsured person, adjusted to Maine, to provide an estimate of the reduction in cost for BD/CC health care expenditures in Maine associated with Dirigo.

In this section, we have described the detailed approach to calculating the Year 4 BD/CC AMCS. We have organized the section into the following:

- Background
- Data Sources and Collection
- Data Compilation and Calculations
- Methods
- Conclusions

BACKGROUND

The negative effects of the lack of health coverage are extensive and well documented. Not only do the uninsured forgo critical medical care and as a result, develop serious chronic conditions and have worse outcomes when obtaining care at later stages of the disease, but they also endure financial hardship and are often unable to pay for the cost of health services received[1,2,3,4]. On average, contributions made by the uninsured toward their medical bills cover an estimated 35 percent of the cost of care delivered by doctors and hospitals[5]. About two-thirds of the BD/CC or "uncompensated care" cost incurred by service providers is passed on to the privately insured in the form of higher premiums while the remaining third is reimbursed through government programs[6]. Thus, improved access to health coverage lays ground not only to a healthier nation, but also translates into effective cost savings.

Maine has attempted to reduce the rate of uninsurance in the State both through aggressive regulation of health care markets and expansion of public program. Regulatory effects include the 1990's "modified community rating" and "guaranteed renewal" and "guaranteed issue" regulations imposed on the private insurance markets. The most recent expansions of public programs are the MaineCare (Medicaid and State Children's Health Insurance Program (SCHIP) programs) expansions that resulted in Maine having one of the more comprehensive public assistance programs for low-income families in the country. Among other groups, Maine extended eligibility to parents and childless adults to income levels above the national level[7]. At the inception of the reform in 2005, about 11.7 percent of the non-elderly Maine residents were without health insurance[8].

Expansions in health coverage started with adoption in 2002 of the Section 1115 HIFA Waiver enabling enrollment for non-disabled, childless adults with incomes within 100 percent of the federal poverty level (FPL) ($10,400 for an individual in 2008)[9,10,11]. By 2005, health coverage

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[1] Institute of Medicine, "Care Without Coverage: Too Little, Too Late" (2002): http://www.iom.edu/CMS/3809/4660/4333.aspx, "Coverage Matters: Insurance and Health Care" (2001): http://www.iom.edu/CMS/3809/4660/4662.aspx, "Hidden Costs, Value Lost: Uninsurance in America" (2003): http://www.iom.edu/en/Reports/2003/Hidden-Costs-Value-Lost-Uninsurance-in-America.aspx

[2] Urban Institute, "Uninsured Americans with Chronic Health Conditions: Key Findings from the National Health Interview Survey" (2001)

[3] Bradbury et al, "Comparing uninsured and privately insured hospital patients: Admission severity, health outcomes and resource use" (2001)

[4] Himmelstein et al. "Illness and Injury as Contributors to Bankruptcy" (2005)

[5] Thorpe, K., "Paying a Premium. The Added Cost of Care for the Uninsured" Families USA report of 2005: http://www.familiesusa.org/assets/pdfs/Paying_a_Premium_rev_July_13731e.pdf

[6] Thorpe, K., "Paying a Premium. The Added Cost of Care for the Uninsured" Families USA report of 2005: http://www.familiesusa.org/assets/pdfs/Paying_a_Premium_rev_July_13731e.pdf

[7] Kaiser Commission on Medicaid and the Uninsured. (2007) "Medicaid Facts", at http://www.kff.org/medicaid/upload/7235-02.pdf (accessed on October 28, 2009)

[8] Weighted tabulations from the March Supplement to the Current Population Survey – See Figure 7 for more details.

[9] 2008 Federal Poverty Guidelines, Department of Health and Human Services: http://aspe.hhs.gov/poverty/08poverty.shtml (accessed on October 28, 2009)

[10] "Maine's Dirigo Health Reform of 2003," State Expansions, Families USA, November 2007: http://www.familiesusa.org/assets/pdfs/state-expansions-me.pdf (accessed on October 28, 2009);

efforts within Dirigo extended income eligibility to parents in MaineCare from 150 to 200 percent of the FPL (from $26,400 to $35,200 for a family of three in 2008)[12].

Dirigo could potentially decrease uninsurance levels in two distinct ways. First, uninsurance could decrease as a result of coverage provided by DirigoChoice, a subsidized health insurance plan for businesses with 50 or fewer employees, the self-employed, and individuals or by the MaineCare Parents Expansion. Thus, this *direct* effect estimates the effect of Dirigo on the level of uninsurance within the eligible population.

One approach to estimating the direct effect of Dirigo on the eligible population would be to simply count the number of individuals enrolled in the DirigoChoice and Parents Expansion programs. This, however, could overstate the impact of Dirigo on the level of uninsurance because these programs' enrollment likely includes both individuals who transitioned from uninsurance and also individuals who transitioned from private insurance. This difference between the number of individuals enrolled in a public program and the reduction in uninsurance rate is often referred to as the "crowding out effect" – the crowding out of private insurance by public insurance. Thus to estimate the true program effect of Dirigo on the number of uninsured in the eligible population it will be necessary to use multivariate estimation approaches.

Also, beyond the direct effect of Dirigo on the level of insurance, there is also a second *indirect* effect. If Dirigo is successful in reducing overall costs in the State of Maine, Dirigo could also reduce the level of uninsurance among higher (ineligible) income groups by reducing the overall cost of health care in Maine and thus reducing insurance premiums from the level where they would have been in the absence of Dirigo. The reduction in premiums and resulting increase in affordability would then lead to an increase in the probability of insurance coverage among all income groups in the State.

It is important to note that this analysis does not hypothesize either that Dirigo reduces health care costs (and thereby health insurance premiums) in either absolute terms or relative to either national or regional averages. It merely hypothesizes that Dirigo reduces health care costs *below what they would have been in Maine without Dirigo*. This counterfactual – average health care costs in Maine in the absence of Dirigo – cannot be directly observed. Instead, we will use statistical models to estimate likely values.

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[11] Suacier, P., "MaineCare and its Role in Maine's Healthcare System," report to Kaiser Commission on Medicaid and the Uninsured from Muskie School of Public Service, January 2005: http://www.kff.org/medicaid/upload/MaineCare-and-Its-Role-in-Maine-s-Healthcare-System-Report.pdf
[12] 2008 Federal Poverty Guidelines, Department of Health and Human Services: http://aspe.hhs.gov/poverty/08poverty.shtml (accessed on October 28, 2009)

DATA SOURCES AND COLLECTION

Appendix B provides a summary of all the steps taken to collect data, compile them, and then analyze resulting datasets to calculate BD/CC savings. These steps are described in detail here on the next few pages.

In Figure 3, we provide a listing of all data sources used for the BD/CC calculation.

Figure 3: BD/CC Data Sources

Data	**Time Period**	**Source – Links accessed – October 28, 2009**
The Annual Social and Economic Supplement (ASEC) to the Current Population Survey		American Standard Code for Information Interchange (ASCII) data from the Census Bureau is made available along with definition statements and dictionary files by the National Bureau of Economic Research:
	Survey Year 1999	http://www.nber.org/cps/cpsmar99.zip http://www.nber.org/data/progs/cps/cpsmar99.do http://www.nber.org/data/progs/cps/cpsmar99.dct
	Survey Year 2000	http://www.nber.org/cps/cpsmar00.zip http://www.nber.org/data/progs/cps/cpsmar00.do http://www.nber.org/data/progs/cps/cpsmar00.dct
	Survey Year 2001	http://www.nber.org/cps/cpschp01.zip http://www.nber.org/data/progs/cps/cpschp01.do http://www.nber.org/data/progs/cps/cpschp01.dct
	Survey Year 2002	http://www.nber.org/cps/cpsmar02.zip http://www.nber.org/data/progs/cps/cpsmar02.do http://www.nber.org/data/progs/cps/cpsmar02.dct
	Survey Year 2003	http://www.nber.org/cps/cpsmar03.zip http://www.nber.org/data/progs/cps/cpsmar03.do http://www.nber.org/data/progs/cps/cpsmar03.dct
	Survey Year 2004	http://www.nber.org/cps/cpsmar04.zip http://www.nber.org/data/progs/cps/cpsmar04.do http://www.nber.org/data/progs/cps/cpsmar04.dct
	Survey Year 2005	http://www.nber.org/cps/cpsmar05.zip http://www.nber.org/data/progs/cps/cpsmar05.do http://www.nber.org/data/progs/cps/cpsmar05.dct
	Survey Year 2006	http://www.nber.org/cps/cpsmar06.zip http://www.nber.org/data/progs/cps/cpsmar06.do http://www.nber.org/data/progs/cps/cpsmar06.dct
	Survey Year 2007	http://www.nber.org/cps/cpsmar07.zip http://www.nber.org/data/progs/cps/cpsmar07.do http://www.nber.org/data/progs/cps/cpsmar07.dct

Data	Time Period	Source – Links accessed – October 28, 2009
	Survey Year 2008	http://www.nber.org/cps/cpsmar08.zip http://www.nber.org/data/progs/cps/cpsmar08.do http://www.nber.org/data/progs/cps/cpsmar08.dct
Health Insurance Revision Extract Files		Detailed explanation of the revision of health insurance figures and guidelines on adjustment of historical data are available from the Census Bureau: http://www.census.gov/hhes/www/hlthins/usernote/usernote3-21rev.html
	Survey Year 1999	http://www.census.gov/hhes/www/hlthins/usernote/extracts/hi_pu_xtrct99.dat
	Survey Year 2000	http://www.census.gov/hhes/www/hlthins/usernote/extracts/hi_pu_xtrct00.dat
	Survey Year 2001	http://www.census.gov/hhes/www/hlthins/usernote/extracts/hi_pu_xtrct01.dat
	Survey Year 2002	http://www.census.gov/hhes/www/hlthins/usernote/extracts/hi_pu_xtrct02.dat
	Survey Year 2003	http://www.census.gov/hhes/www/hlthins/usernote/extracts/hi_pu_xtrct03.dat
	Survey Year 2004	http://www.census.gov/hhes/www/hlthins/usernote/extracts/hi_pu_xtrct04.dat
State Income Eligibility Guidelines: Medicaid and SCHIP		Income eligibility thresholds data were collected by the Kaiser Foundation and published in a series of annual state reports titled: "A 50 State Update on Eligibility Rules, Enrollment and Renewal Procedures, and Cost-Sharing Practices in Medicaid and SCHIP." Data on child income eligibility thresholds are presented in Table 1 of the report "State Income Eligibility Guidelines: Medicaid for Children and CHIP-funded separate state programs[13]." Eligibility thresholds for parents appear in Table 3 of the report: "Income Thresholds for Jobless and Working Parents Applying for Medicaid."
	Survey Year 2000	http://www.kff.org/medicaid/loader.cfm?url=/commonspot/security/getfile.cfm&PageID=13443

[13] The title of the table varies slightly from year to year

Data	Time Period	Source – Links accessed – October 28, 2009
	Survey Year 2001	http://www.kff.org/medicaid/loader.cfm?url=/commonspot/security/getfile.cfm&PageID=14125
	Survey Year 2002	http://www.kff.org/medicaid/loader.cfm?url=/commonspot/security/getfile.cfm&PageID=14355
	Survey Year 2003	http://www.kff.org/medicaid/loader.cfm?url=/commonspot/security/getfile.cfm&PageID=14355
	Survey Year 2004	http://www.kff.org/medicaid/upload/Beneath-the-Surface-Barriers-Threaten-to-Slow-Progress-on-Expanding-Health-Coverage-of-Children-and-Families-pdf.pdf
	Survey Year 2005	http://www.kff.org/medicaid/upload/In-a-Time-of-Growing-Need-State-Choices-Influence-Health-Coverage-Access-for-Children-and-Families-Report.pdf
	Survey Year 2006	http://www.kff.org/medicaid/upload/7608.pdf
	Survey Year 2007	http://www.kff.org/medicaid/upload/7740_ES.pdf
	Survey Year 2008	http://www.kff.org/medicaid/upload/7855.pdf
HHS Poverty Guidelines		The poverty guidelines are issued annually in the Federal Register by the Department of Health and Human Services and represent a simplification of the poverty thresholds for use for administrative purposes- determining financial eligibility for federal programs. Further information on development and use of poverty guidelines could be obtained from DHHS: http://aspe.hhs.gov/poverty/faq.shtml#differences
	Survey Year 2000	http://aspe.hhs.gov/poverty/99poverty.htm
	Survey Year 2001	http://aspe.hhs.gov/poverty/00poverty.htm

Data	Time Period	Source – Links accessed – October 28, 2009
	Survey Year 2002	http://aspe.hhs.gov/poverty/01poverty.htm
	Survey Year 2003	http://aspe.hhs.gov/poverty/02poverty.htm
	Survey Year 2004	http://aspe.hhs.gov/poverty/03poverty.htm
	Survey Year 2005	http://aspe.hhs.gov/poverty/04poverty.shtml
	Survey Year 2006	http://aspe.hhs.gov/poverty/05poverty.shtml
	Survey Year 2007	http://aspe.hhs.gov/poverty/06poverty.shtml
	Survey Year 2008	http://aspe.hhs.gov/poverty/07poverty.shtml
State Federal Information Processing Standard (FIPS) Codes		State FIPS codes crosswalk was obtained from the Bureau of Labor Statistics: http://www.bls.gov/lau/lausfips.htm
Medical Expenditure Panel Survey	2002	Data, definition files and documentation were obtained from the Agency for Health Care Research and Quality: http://www.meps.ahrq.gov/mepsweb/data_stats/download_data_files_detail.jsp?cboPufNumber=HC-070
Per Capita National Health Expenditures	2002	The Office of the Actuary in the Centers for Medicare & Medicaid Services annually produces projections of health care spending for categories within the National Health Expenditure Accounts, which track health spending by source of funds (for example, private, Medicare, Medicaid) and by type of service (hospital, physician, prescription drugs, etc.). http://www.cms.hhs.gov/NationalHealthExpendData/downloads/nhe65-18.zip

DATA COMPILATION AND CALCULATIONS

The Annual Social and Economic Supplement (ASEC) to the Current Population Survey (CPS) was the primary source of data used in the evaluation of the effect of the Dirigo reform on uninsurance rate in Maine. Core datasets prior to the 2005 year survey were edited following the Census guidelines[14] to incorporate improvements in the health insurance survey instrument resulting in consistent insurance data series over the study period from 2000 to 2008. Additionally, these data were supplemented with the Medicaid and SCHIP income eligibility thresholds[15] from the Kaiser foundation report series "A 50 State Update on Eligibility Rules, Enrollment and Renewal Procedures, and Cost-Sharing Practices in Medicaid and SCHIP" and poverty guidelines from the Department of Health and Human Services (DHHS).

At the time **srHS** completed this analysis (analysis conducted in the first and second quarters of calendar year 2009) for BD/CC, **srHS** used the most recent data available at that time. For example, as noted above, the primary source of data for BD/CC is the CPS and **srHS** used the most recent CPS data available at that time – Survey Year 2008 covering 2007. On September 28, 2009, the Census Bureau released Survey Year 2009 covering 2008. We have not incorporated the 2009 survey results in to our analysis as of the time of this report. We have included the Survey Year 2009 data[16] as part of the documentation for this report.

Data Compilation Summary

The CPS is a national survey designed primarily to establish national trends in community characteristics, such as the unemployment rate. However, the CPS data are regularly used to make estimates of the number and rate of uninsured persons at the state level. The family unit employed in the analysis is constructed using CPS sub-family definitions to include adults plus those family members who typically would be eligible for coverage under family health insurance plans. As such, a family unit includes the head of the sub-family, spouse, and own/related children under age 19, as well as children under 24 who are enrolled in school full-time. Thus eligibility criteria that relate to family structure are identified through relationships within the constructed family unit. Further, family poverty status is induced based on the sum

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[14] Detailed explanation of the revision of health insurance figures and guidelines on adjustment of historical data are available from the Census Bureau: http://www.census.gov/hhes/www/hlthins/usernote/usernote3-21rev.html

[15] Medicaid eligibility thresholds varied by child's age (0-1,2-5,6-16,17-19 in 2000 and 2001 analysis; 0-1,2-5,6-17,18-19 in 2002; 0-1,2-5,6-19 in 2003-2008) and parent work status (working versus non-working); A single income threshold was used to ascertain SCHIP eligibility for children

[16] CPS Survey Year 2009:
http://www.nber.org/cps/cpsmar09.zip
http://www.nber.org/data/progs/cps/cpsmar09.do
http://www.nber.org/data/progs/cps/cpsmar09.dct

of total personal income of all members of the family and unit size compared against the state/year/unit size-specific poverty guidelines as issued by the US Department of Health and Human Services.

To identify eligibility criteria for Medicaid, we used program descriptions from the Kaiser Family Foundation. The Kaiser Family Foundation has collected detailed data on eligibility criteria by state, with eligibility defined by age and income. Using these definitions, we coded eligibility for both Medicaid and SCHIP for every state. Additionally, we coded eligibility for Dirigo and Medicaid in the CPS data, from 2000-2008 (i.e., individual-level variables). There were a number of programming challenges in this process. The CPS data are based on households, which may or may not incorporate multiple families. The key challenge is that some variables are related to the particular individual interviewed (such as age or gender) and other variables are based on the "family" unit, such as income or, critically, insurance eligibility. Within the CPS, for each year we developed algorithms identifying both the individual and what we termed the "health insurance unit". This is a complex algorithm. The reason it is so important is that eligibility for public programs is not based on (for example) individual income, but is based on "family" income. Using the individual's income, therefore, would grossly overstate eligibility for public programs, particularly for children, who typically have no income. However, because the data are based on households, which may contain multiple unrelated families, using all income within a household would overstate income and understate eligibility.

These problems exist whenever using the CPS and researchers have developed standardized approaches to identifying health insurance units[17]. We utilized these standard approaches to identify individuals who, for the purposes of health insurance, would be considered a single unit (hence the term "health insurance unit"). This was based on marital and child-parent relationships, among other factors. The resulting dataset has information on the individual level (e.g., age, gender, insurance status), the health-insurance-unit level (e.g., income, presence of a worker in the family, whether child/parent is eligible for Medicaid or SCHIP, etc.), the county level (e.g., doctors per capita, unemployment rate), and the state level (e.g., HIFA eligibility, Medicaid eligibility, SCHIP eligibility).

Estimates pertinent to BD/CC were produced using data from the 2002 Household Component to the Medical Expenditures Panel Survey (MEPS) following previously published methodology discussed in Thorpe (2005).

Detailed Data Compilation Discussion

A detailed log documenting all steps in data cleaning and recode is available in the documentation package in the file named, crdata_ dirigo_052009_documentation.xls.

[17] Urban Institute accessed October 28, 2009
http://www.urban.org/pubs/state_level_data/stdbint.html

- **The Annual Social and Economic Supplement (ASEC) to the Current Population Survey**

  The ASEC is a March Supplement to the Current Population Survey (CPS) collected annually by the Bureau of the Census for the Bureau of Labor Statistics. The survey is the primary source of detailed information on labor force characteristics of the U.S. population. Along with employment data, the supplement fulfills a secondary role in providing information on demographic characteristics, family structure, health insurance, educational attainment, income and work schedules making it an invaluable resource often employed by the government policy makers, legislators and academics alike in development of economic indicators, planning and evaluation of government programs.

  A sample of approximately 50,000-100,000 households is selected annually by a multistage stratified statistical sampling scheme to be representative of the civilian non-institutionalized population in the US. The sample provides estimates for the nation as a whole and serves as part of model-based estimates for individual states and other smaller geographic areas[18].

  Given the scope of the analysis, the data were subset to non-elderly population under the age of 65 resulting in 1,650,820 observations or an average annual subset of 117,000 records over the study period from 2000 to 2008.

  Based on set CPS family identifiers, Health Insurance Units (HIUs) were defined and used as a relevant family unit in our analysis. Like conventional CPS family grouping, HIU includes only members related by birth, marriage, or adoption residing together; however, unlike the CPS family, HIU also includes never married foster children under the age of 19 and pushes out, into a separate HIU unit, members of related subfamilies, including children over 18 residing with parents. Constructed in this manner, an HIU helps better assess individuals' access to health insurance coverage capturing a realm of family members within the household that would customarily be eligible for coverage by a family plan.

  For the most part, analytical variables were created by selecting a relevant category in the raw CPS variable or by computing a summary measure on HIU, household, or county level; or alternatively, by imputing values based on responses of other HIU members as in parent characteristics. The following person level demographic and socio-economic variables were defined for all observations regardless of age: head of household identifier, an indicator for child or parent observation, age group (for adults 5 categories were created: "under 19", "19-29", "30-39", "40-49", "50-65"; for children age 4 categories were defined: "under1", "1-5", "6-16", "17-18"), race and ethnicity ("White Non-Hispanic", "Black Non-Hispanic", "Other Non-Hispanic", "Hispanic"), nativity ("US born or born to US parents", "Foreign"), marital status ("Married- not living with spouse", "Married- living with spouse", "Widowed, divorces, separated", "Never married"), educational load ("Full-time student", "Not a

[18] For further details refer to the U.S. Census Bureau: http://www.census.gov/apsd/techdoc/cps/cps-main.html

student" or "Part-time student"), disability status, insurance status ("Private insurance", "Public insurance", "Uninsured"), a dummy variable for receipt of public assistance, Medicaid and SCHIP income eligibility threshold, and lastly geographic identifiers including an indicator for households that change states within the survey reference period, current state of residence ("Maine", "all other"), region of residence ("North East", "all other"), Census Division ("New England", "all other") and FIPS county code.

Variables related to labor force participation including worker identifier (equal to 1 if positive wages were reported, and zero otherwise), type of employment ("Self-employed" and "Government Employed"), union worker and union job identifiers, work load ("Part-time" ,"Full-time", "Hourly Worker" dummies), establishment size ("NIU", "Under 10", "10 - 24", "25 - 99","100 - 499","500 - 999","1000+") were defined for adults only. Parent employment, educational attainment, and marital status data were further summarized on the HIU unit and allocated across all related children, such that if at least one parent works then the parent work status identifier will be set to 1 for all children in HIU.

HIU variables including HIU size, number of children, and income were obtained by summarizing the relevant field across all HIU members. HIU income, family size and state data was further used to impute HIU relative poverty status by dividing HIU income by the relevant poverty guideline. It should be noted that income questions in the CPS refer to income prior to the survey collection, in other words in 2000 CPS data we observe income as of 1999; thus in assigning poverty status, 1999 poverty guideline was used with 2000 CPS data.

Additionally, we created a set of county variables by computing weighted average unemployment rate, percent work force distribution by establishment size ("Under 10", "10 - 24", "25 - 99","100 - 499","500 - 999","1000+"), and poverty prevalence. These summary measures were estimated on a full population set, including those over 64 years of age, and were further merged with the core annual subsets by county identifier. Observations with missing county identifier (ID) variable were grouped into "Unknown County".

Throughout the study period there have been changes in definition of several core variables, including race, insurance status, and state. Where available, census guidelines were employed to produce consistently defined data series.

- *Race Recode*
  Prior to 2003, race was grouped by four mutually exclusive categories, distinguishing between "White", "Black", "American Indian, Aleut Eskimo" and "Asian or Pacific Islander". Staring with 2003 survey twenty one categories were introduced to define one's race as follows: 1 "White only", 2 "Black only", 3 "American Indian", 4 "Asian only", 5 "Hawaiian/Pacific Islander", 6 "White-Black", 7 "White-AI", 8 "White-Asian", 9 "White-HP", 10 "Black-AI", 11 "Black-Asian", 12 "Black-HP", 13 "AI-Asian", 14 "Asian-HP", 15 "White-Black-AI", 16 "White-Black-Asian", 17 "White-AI-Asian", 18 "White-Asian-HP", 19 "White-Black-AI-Asian", 20 "2 or 3 races", 21 "4 or 5 races". To create a race field consistently defined across all survey years, we first pulled out Hispanics -

respondents selecting Spanish/Mexican ethnicity, into a separate race category and then collapsed detailed race grouping into four mutually exclusive categories as follows: 1 "White Non-Hispanic" 2 "Black Non-Hispanic" 3 "Hispanic" 4 "Other."

- **Health Insurance Supplemental Files**

  As a result of revisions on the instrument used to administer the Annual Social and Economic Supplement (ASEC) to the Current Population Survey (CPS) the Census Bureau established that under certain circumstances, information provided by respondents was not fully recognized by the editing system. The questionnaire asked which household members had an insurance policy (either through an employer/union or a privately purchased plan) in their own name. If a plan was reported, questions then asked whether anyone else was covered by this plan, and if so, which other household members were covered. Interviewers could either report, person by person, every other person that was covered or they could simply make an indication that "all" other household members were covered. In original form, the process always accepted respondents who reported every other person covered by a plan; it did not, however, recognize the "all other household members were covered" response. Instead, those cases were imputed coverage.

  Beginning in 2005, the Census modified the process that assigns employment-based and private direct-purchase health insurance coverage to non-policy holders producing more accurate estimates of health insurance. To facilitate trend analyses of insurance indicators the Bureau released a set of Health Insurance Revision files that could be used to produce consistent data series starting with 1999 year survey through the most recent extracts. Annual revision files were merged with core CPS data from 1999- 2004 by unique family identifier, adding information on coverage of all family members by either private or employer-sponsored insurance. Additional data were incorporated in defining insurance status of respondents prior to 2005.

- **Medicaid and SCHIP Eligibility Data**

  Income eligibility thresholds data were collected by the Kaiser Foundation and published in a series of annual state reports titled: "A 50 State Update on Eligibility Rules, Enrollment and Renewal Procedures, and Cost-Sharing Practices in Medicaid and SCHIP." Data on child income eligibility thresholds are presented in Table 1 of the report "State Income Eligibility Guidelines: Medicaid for Children and CHIP-funded separate state programs[19]." Eligibility thresholds for parents appear in Table 3 of the report: "Income Thresholds for Jobless and Working Parents Applying for Medicaid." Using Kaiser reports, we constructed a STATA[20] dataset containing annual Medicaid/SCHIP income eligibility thresholds by age group and parent work status for each of the states across all study years from 2000 through 2008. Since no Medicaid income eligibility data were available for parents prior to 2002, 2002 thresholds were used to ascertain parent Medicaid eligibility in 2000 and 2001. Based on

[19] The title of the table varies slightly from year to year
[20] STATA is a statistical programming software

report availability, there was a slight mismatch between the survey data and the span of eligibility data. We used the 2000 report to ascertain Medicaid income eligibility for 2000 survey, the 2002 report for 2001 survey, the 2003 report for 2002 and 2003 surveys, the 2004 report for 2004 survey, the 2005 report for 2005 survey, the 2007 report for 2006 survey, the 2008 report for 2007 survey, and the 2009 report for 2008 survey.

- **State FIPS codes**

  In 2000 CPS data, the state variable is defined using Census state code. We converted the latter definition to Federal Information Processing Standard (FIPS) convention by creating a crosswalk dataset containing Census state code and FIPS state definition and merging it back with the core CPS data for 2000. The State FIPS codes crosswalk was obtained from the Bureau of Labor Statistics: http://www.bls.gov/lau/lausfips.htm.

- **Medical Expenditure Panel Survey**

  Data from the Medical Expenditure Panel Survey (MEPS) from 2002 were used to compute the ratio of the mean uncompensated care among the elderly to the non-elderly population mean following the methodology developed in Thorpe[21] (Thorpe (2005)). The Medical Expenditure Panel Survey is a set of large-scale surveys of families and individuals, their medical providers (doctors, hospitals, pharmacies, etc.), and employers across the United States (US). MEPS data are collected by the Agency for Health Care Research and Quality (AHRQ) and provides nationally representative estimates of health care spending, insurance status, utilization of medical services, sources of payment, and disease prevalence along with a broad set of socio-economic characteristics for the non-institutionalized civilian population in the US.

- **Per Capita National Health Expenditures**

  The Office of the Actuary in the Centers for Medicare & Medicaid Services annually produces projections of health care spending for categories within the National Health Expenditure Accounts, which track health spending by source of funds (for example, private, Medicare, Medicaid) and by type of service (hospital, physician, prescription drugs, etc.). We used 2005 and 2008 per capita National Health Expenditures data to inflate estimates of per capita uncompensated care as reported in Thorpe from 2005 to 2008. Historical National Health Spending data could be accessed through Centers for Medicare and Medicaid Services as follows:
  http://www.cms.hhs.gov/NationalHealthExpendData/downloads/nhe65-18.zip

[21] Thorpe, K., "Paying a Premium. The Added Cost of Care for the Uninsured" Families USA report of 2005, also referred to as Thorpe (2005) throughout report :
http://www.familiesusa.org/assets/pdfs/Paying_a_Premium_rev_July_13731e.pdf

METHODS

The purpose of this analysis is to estimate the relationship between Dirigo and the amount of bad debt and charity care (BD/CC) provided by Maine health care providers. To do this, it is first necessary to estimate the statistical significance and strength of the relationship between Dirigo and the number and rate of uninsured for health care in the State of Maine. The basic estimation task is to compare the experience of individuals in the target population who were exposed to Dirigo to the experience of individuals in the target or pseudo-target populations who were not exposed to Dirigo. The key challenge is that subjects were not assigned randomly to treatment and control groups. In an ideal study, we would be able to randomly assign individuals to Dirigo and "not Dirigo". In the absence of randomization, we must find suitable control groups. Thus, two important tasks in the evaluation are careful identification of treatment groups and identification of suitable control groups.

By "treatment group", we mean the group of individuals who plausibly could be affected by the Dirigo program. Careful identification of the treatment groups is necessary to avoid biased estimates of program effects. Dirigo itself could

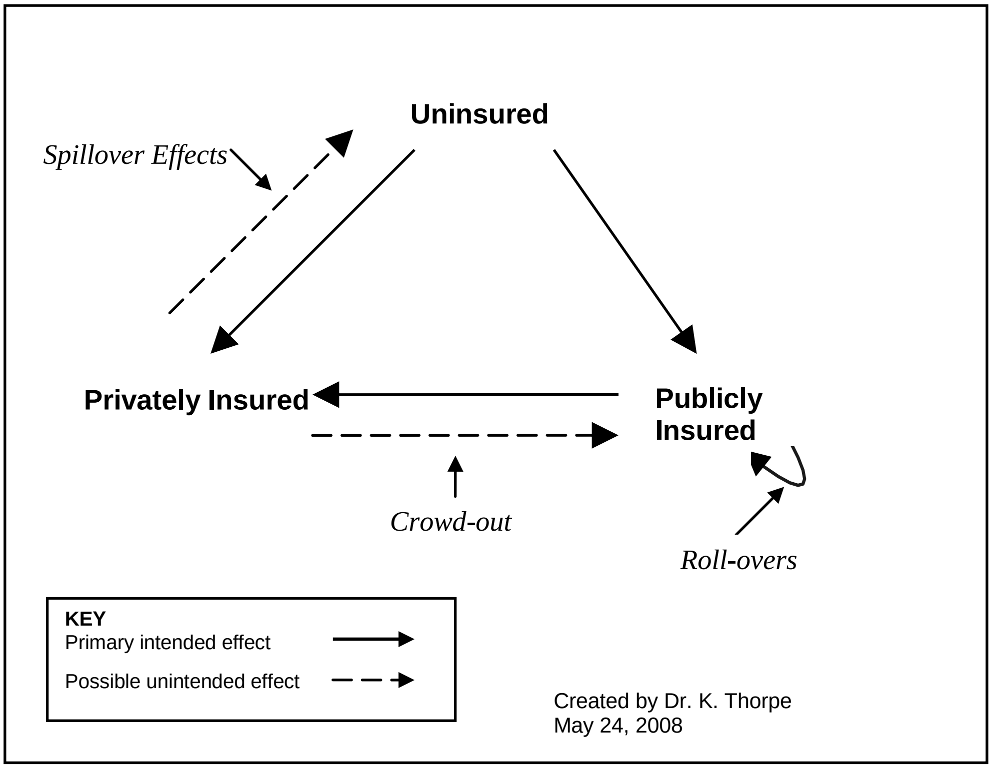
1) draw uninsured individuals into the private insurance market by reducing the cost of health care and thus insurance premiums,
2) draw people from public insurance programs to private insurance, either to avoid the stigma of welfare or to gain improved access to services,
3) draw uninsured individuals into public insurance (Dirigo), or
4) draw privately insured individuals into the public Dirigo program.

These consequences may or may not be intended, and they illustrate the need to think broadly about the definition of the target population in this evaluation.

Figure 4 below shows the relationship among the insurance categories of interest in the evaluation. The figure shows that the primary intended Dirigo effects are to move individuals from the uninsured to public insurance (through benefit and eligibility expansions) and from the uninsured to private insurance (through premium reductions via cost reductions). However, the interventions could have unintended effects. Crowd-out occurs when privately insured individuals move to public insurance as a result of the Dirigo interventions. Spill-over effects include movement from private insurance to uninsurance as a result of changes in employer insurance policies associated with the Dirigo interventions. Finally, roll-over suggests movement from one public insurance program to another public insurance program, e.g., from a Medicaid program to a Dirigo program.

The figure is not meant to imply that all movement among these categories is the result of Dirigo. In each case, there are secular trends at work, as well. Separating the effects of Dirigo from secular trends requires the careful specification of control groups.

Figure 4: Relationship among Insurance Categories



Any evaluation including a treatment group must answer the question, "Compared to what?" The general answer is, "Compared to the control group". The purpose of the control group is to provide information on the experience of a member of the target population in the absence of the intervention. Control groups often are said to provide information on the "secular trend" in the dependent variable – another way of saying what the experience of the treatment group would have been in the absence of the demonstration. Secular trends are particularly important in this study because nationally, both the number of uninsured individuals and enrollment in Medicaid and SCHIP were increasing after the enactment of Dirigo.

One strategy that was not feasible in the national datasets used in this evaluation was for individuals to serve as their own controls, i.e., observing the same individual in both the pre-implementation and post-implementation time periods. The national datasets are not true panel data sets[22]. Even if the same individuals were observed for a few consecutive years, the number of individuals spanning years before and after implementation of Dirigo is quite small since the CPS data is a sample.

[22] Panel data refers to a data set in which the same unit of observation (e.g., a person or a state) is observed at multiple points in time.

Some statistical analysts refer to the information provided by the control group as a "counterfactual". Pure counterfactuals are impossible to establish because it never is possible to observe the same subject experiencing and not experiencing the treatment at exactly the same point in time. The perfect control group is a group that is identical to the treatment group in every respect, except for the fact that the control group was not exposed to the intervention. Thus, all control groups are an approximation to the ideal.

The gold standard for control groups is that found in large randomized trials, and even in randomized trials, the validity of the control group can be threatened by selective attrition. In randomized trials, individuals in the target populations are assigned randomly to the treatment and control groups. Because randomization was not possible in this evaluation, our analysis was limited in certain ways. Lack of randomization introduces the possibility of omitted variables bias. The difficulties associated with non-randomization are alleviated to the extent that the control groups provide good estimates of the experience of individuals like those in the treatment groups in the absence of Dirigo. We also addressed this concern by including a fixed effect for each state to capture time-invariant differences among states.

To explain our estimation approach, we begin with a simple linear model as a heuristic device. Later we discuss complications that arose when insurance status was treated as a binary dependent variable. Our basic model is:

$$Y_{ijt} = X_{ijt}\,\beta + \beta_T T_{ij} + \beta_P P_{ijt} + \beta_I\,[T_{ij} \text{ x } P_{ijt}] + u_{ijt} \qquad \text{--} \qquad (1)$$

where the subscripts i, j and t stand for the i^{th} individual in the j^{th} state in the t^{th} time period. Let t indicate the post-intervention time period and t-1 indicate the pre-intervention time period, and:

Y = 1 if the individual is insured and 0 otherwise

X = a set of control variables, including an intercept term

T = a set of variables representing treatment and control groups as described below.

P = 1 if the observation is from the post-implementation period and 0 if the observation is from the pre-implementation period

u = unobserved error.

In this model, T is a binary variable equal to 1 if the subject is in the treatment group and 0 if the subject is in the control group. The difference between the post- and pre-implementation values of Y for the treatment group is:

$[X_{ij,t} - X_{ij,t-1}]\ \beta + \beta_T + \beta_P$.

The difference between the post- and pre-implementation values of Y for the control group is:

$[X_{ij,t} - X_{ij,t-1}]\ \beta + \beta_T + \beta_P + \beta_I$.

Thus, the difference in these two differences, which is the "treatment effect", is β_I. This model is known in the econometrics literature as a standard "difference in differences" model.

Thus far, we have discussed the outcome variable (insurance status) as though it were a continuous variable, in order to simplify the discussion of some of the estimation issues. Clearly, insurance status is not continuous, but discrete. A simple way to improve the specification of the insurance variable is to treat it as a binary (0, 1) variable. The change to a binary dependent variable does not affect most of our discussion of methods. Both logit and probit estimators are the conventional choices for analysis of binary dependent variables, and models that incorporate binary dependent variables into random and fixed effects models have been explored in some depth (e.g., Greene, 2003, pp. 689-700[23]). Our main results are based on a fixed effects logit model, with state level fixed effects. However, we examined the sensitivity of our results to different model specifications (presented later in this section) and found that the results were robust to different model specifications.

Our national dataset is not true panel data in the sense that we do not observe the same individual at multiple points in time. However, the intervention is measured at both the state and individual level, and we do observe samples of individuals from the same states over time, creating state-specific or year-specific effects that result in error terms[24] being correlated among the observations in our data. Correlations among error terms reduce the amount of statistically *independent* data available to estimate the treatment effect, and thus reduce statistical power. Failure to account for such correlations can lead to erroneous conclusions – suggesting that an estimated treatment effect is statistically significant, when it is not. These correlations can be shown by rewriting the error term in equation (1) as u^*_{ijt} and then expanding it as follows:

$$u^*_{ijt} = u_t + u_j + u_{ijt}$$

where u_t is the time-specific component of the error term, u_j is the state-specific component of the error term, and u_{ijt} is the time-, state-, and individual-specific error term. The time and state effects can be modeled with either a fixed or random effect. We included a fixed state effect and included time as a continuous variable to minimize the multicollinearity between the difference-in-differences estimator and the time effect.

In order to conserve space and simplify the presentation of our results, we report the "marginal effects" of each of our explanatory variables on the dependent variable, rather than the coefficients themselves or odds ratios. Y is the dependent variable that represents (a) the

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[23] Greene, William (2003). Econometric Analysis. Pearson Prentice Hall: Upper Saddle River, New Jersey (2003).
[24] Variable used in regression modeling to address variation in the dependent variable not explained by the independent variables

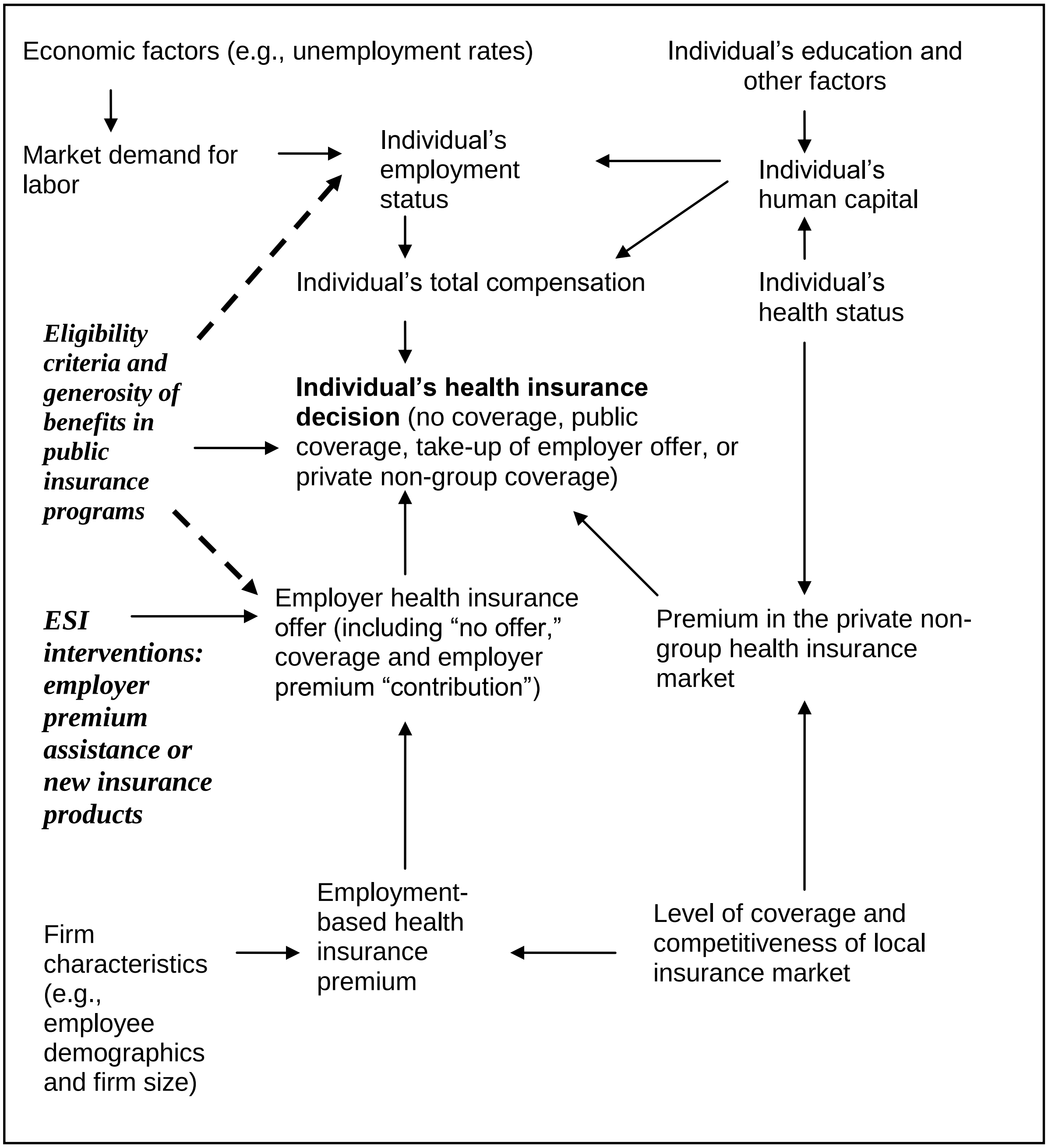
probability of having insurance, or (b) the probability of being uninsured, having public insurance, or having private insurance. The marginal effect of X on Y is the percentage-point change in the probability associated with a one unit change in the explanatory variable.

Selection of explanatory variables

Our explanatory variables were selected based on a conceptual model which explains factors associated with individuals having health insurance[25,26,27,28,29,30,31]. Figure 5 shows a diagrammatic summary of some of the important variables and their relationships to the individual's health insurance status. The variables in the figure reflect the discussion of control variables in the Data section.

[25] Cutler, D., Gruber, J. (1996). "Does Public Insurance Crowd Out Private Insurance?": http://ideas.repec.org/a/tpr/qjecon/v111y1996i2p391-430.html
[26] Cutler, D., Gruber, J. (1996). "The Effect of Medicaid Expansions on Public Insurance, Private Insurance, and Redistribution." The American Economic Review. 86(2): 378-383
[27] Dubay, L., Kenney, G. (2003). "Expanding Public Health Insurance to Parents: Effects on Children's Coverage Under Medicaid." Health Services Research. 38(5): 1283-1301
[28] Holahan, J., Uccello, C., Feder, J., Kim, J. (2000). "Children's Health Insurance: The Difference Policy Choices Make." Inquiry. 37(1): 7-22
[29] Kenney, G., Holahan, J. (2003). "Public Insurance Expansions and Crowd Out of Private Coverage." Medical Care. 41(3): 337-340
[30] Lo Sasso, A.T., Buchmueller, T.C. (2004). "The Effect of the State Children's Health Insurance Program on Health Insurance Coverage." Journal of Health Economics. 23:1059-1082
[31] Marquis, S.M., Long, S.H. (2003). "Public Insurance Expansions and Crowd Out of Private Coverage." Medical Care. 41(3): 344-356.

Figure 5: Factors affecting the individual's health insurance decision



The model is organized so that factors affecting the individual's employment status and income earning potential work from the top of the diagram down, while factors affecting the employer's decision to offer health insurance, and the terms of that offer, work from the bottom of the diagram up. Also included are the characteristics of public insurance programs. These factors converge in the middle of the diagram to produce the variable of interest in evaluation: the individual's decision regarding health insurance (shown in bold-faced type). The choices are subsumed into an insurance yes/no dichotomous variable.

There are two causal arrows of particular interest in the diagram, indicated by dashed lines. These arrows capture concerns regarding unintended consequences of the Dirigo intervention, specifically that changes in the generosity of public programs could affect either: 1) the individual's employment status, or 2) the employer's premium contribution or decision to offer health insurance.

Some individuals in poor health who fall outside the pre-implementation eligibility requirements for public insurance may remain in the workforce primarily to maintain access to group health insurance rates. When public insurance eligibility criteria are loosened under Dirigo, however, some of those individuals may leave the workforce. This is shown via the dashed arrows is to make the individual's employment decision and the employer's health insurance offer decision *mediating* variables that lie on the causal pathway between Dirigo and the individual's insurance decision. If the individual's employment decision and the employer's health insurance offer decision are *included* in analyses of the effect of public program generosity on the individual's insurance decision, then those *indirect* effects of benefit generosity on the individual's insurance decision will be eliminated from the estimated effect of public program generosity on the individual's insurance decision. The estimated effect will be the *partial* effect of public program generosity, *controlling for* the individual's employment decision and the employer's health insurance offer decision. These partial effects could be larger or smaller in magnitude and statistical significance than the effects that include the mediating variables. This example provides another illustration of the importance of model-driven statistical analyses.

The conceptual model provides a general guide to the types of variables included in the model:

- Individual-level demographic characteristics such as age, race, sex, education, employment status, health, home stability, and characteristics of employment-based health insurance offers, and
- Characteristics of the market area, such as the unemployment rate and characteristics of employers.

Figure 6 presents an overview of variables found to be significantly associated with uninsurance rates in previous literature. Because so many of the previous studies used the CPS, we were able to incorporate many of the variables (denoted with an asterisk) shown in Figure 6 below in our regression. For the one type of variables for which we did not include the majority, area characteristics (also described as community variables in this report), we tested the sensitivity of the model to their presence and found they did not add materially to the explanatory power of the model.[32]

[32] Appendix G includes a description of the sensitivity analyses conducted on the model specifications, including testing the sensitivity to the community variables listed in the table below as area characteristics.

Figure 6: Independent Variables used in Previous Studies

Family Characteristics	Adult Characteristics	Child Characteristics	Area Characteristics
Income*	Age*	Age*	Physicians per 1,000 in County
Welfare History	Gender*	Gender*	County/State Per Capita Income*
Household Size*	Race*	Race*	County/State Per Capita Income (prior year)
Number of Children*	Activity Limitations (disability)*	Health Status	County/State Unemployment Rate*
Infant Children (Y/N)	Citizenship		County/State Unemployment Rate (prior year)
Moved in Past 12 Months*	Foreign Born*		Medicare Reimbursement Rate (relative to national median)
MSA (urban) residence*	Interview in Spanish (proxy for recent immigration)		Average Family Contribution Toward Family ESI Premium
Head of Household*	Education*		HMO Penetration in County/State
Number of Workers	Marital Status*		Managed Care Enrollment
Total Number in Household in Fair/Poor Health	Work Status*		Region of Country
	Firm Size*		Medicaid Enrollment Rate
	Government Worker*		SCHIP Enrollment Rate
	Self-Employed*		Labor Force Participation
	Health Status		Marginal Tax Rates
	Recently Pregnant		Welfare/Poverty Caseload
	Risk Aversion		State*
	Offer of Employer Sponsored Insurance (ESI)		Year*

* Included within regression modeling specifications

Using the CPS, we were able to include in our analysis many of the variables listed in Figure 6. For adults, we included variables related to sociodemographic characteristics (gender, indicator variables for age categories, race, marital status, education, disability), household characteristics (whether the individual was the head of household, the household size, whether the individual was born in the United States, number of children in the household, income), employment characteristics (whether the individual was a student, employed, size of employer, whether job was unionized or government) and characteristics of the county of residence that have been found to be related to insurance coverage (in a metropolitan area, county unemployment rate, county income, county employer characteristics).

For children, we modified the variables somewhat. Instead of including the individual's employment characteristics, for example, we included the employment characteristics of the head of household (because most children are not in the workforce). Similarly, education level is measured for the head of household. Other variables are measured for the child directly, such as age, gender, and race.

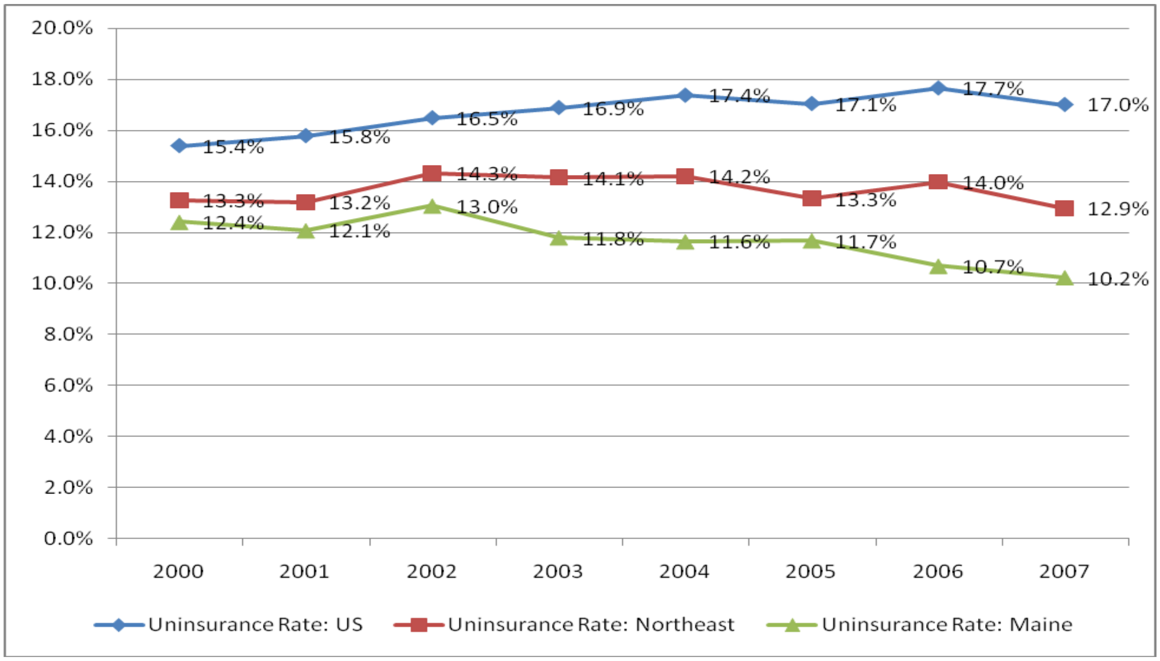
Findings

A. Trends in Access to Health Coverage

From 2000 to 2007, the uninsurance rate in Maine was one of the lowest in the nation; over 20 percent below the national average in the years prior to Dirigo and 40 percent less than the national rate in 2007 (17.0 percent and 10.2 percent, respectively). The implementation of the Maine HIFA Waiver marked the early stages of the reform with enrollment into MaineCare extended to "childless adults" in late 2002[33]. There was a significant (10 percent) drop in the rate of uninsured in Maine from 2002 to 2003 (Figure 7). The lower level of uninsurance was further sustained over the following three years, averaging about 11.7 percent a year, with a subsequent reduction in uninsurance rate to 10.67 percent in 2006. The latter coincides with the Medicaid expansion efforts of 2005, enabling access to public assistance for parents with incomes in between 150 and 200 percent of the FPL (from $26,400 to $35,200 for a family of 3 in 2008). Percentages of those insured increased yet more with the launch of the DirigoChoice Program that same year, 2005, targeting small businesses and individuals with no access to employer sponsored insurance in families with incomes below 300 percent of the FPL. See Figure 8 for DirigoChoice and MaineCare Parent Expansion historical enrollment.

[33] Kaiser Commission on Medicaid and the Uninsured, "Maine Section 1115 Waiver," at http://www.kff.org/medicaid/loader.cfm?url=/commonspot/security/getfile.cfm&PageID=14327

Figure 7: Overall Trends in Uninsurance: United States, Northeast, and Maine



Source: Tabulations from the 2000-2008 March Supplement to the Current Population Survey.
Notes: The data are restricted to persons under 65 and weighted with the person level weights. "Uninsured" is defined as persons reporting no sources of health coverage and who are not covered as dependents under policies of other family members. Northeast region includes Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut, New York, New Jersey, and Pennsylvania.

Figure 8: DirigoChoice and MaineCare Parent Expansion Enrollment[34]

Year	Average DirigoChoice Enrollment	Average MaineCare Parent Expansion Enrollment	Total
2005	5,613	3,659	9,272
2006	10,540	4,998	15,538
2007	14,353	5,490	19,843
2008	12,019	5,582	17,601
Average, 2005-2007	10,169	4,715	14,884

Expansions in access to health coverage in Maine over the period are particularly evident when contrasted against the national trend and, to a lesser extent, the trend in the Northeast region as a whole. While the rate of uninsured in Maine *decreased* at an average rate of about 1.3

[34] Received from DHA – see file: Dirigo Choice and MC Exp Par Enrollment.xls

percent annually, there was about 0.8 percent annual *increase* in the uninsurance rate in the nation throughout the post-Dirigo period (2005-2007). Although the region showed a similar overall trend, the Maine effect was more than double the average regional effect.

On key variables associated with health insurance, Maine was relatively stable between 2000 and 2007; see Figure 9 below. Minorities went from 2.3% of the population to 2.5%. The proportion of the population defined by the CPS as a worker was relatively steady (78.4% to 76.9%)

Figure 9: Descriptive Statistics, Maine, 2000-2007

	2000	2001	2002	2003	2004	2005	2006	2007
Uninsured	14.0%	14.3%	15.1%	14.1%	13.9%	13.0%	12.4%	12.1%
Female	50.0%	51.0%	49.8%	50.8%	50.8%	49.7%	50.1%	50.2%
Age Under 19	1.0%	0.7%	1.3%	1.8%	1.4%	1.7%	1.1%	1.0%
Age 19-29	20.8%	19.7%	21.7%	21.0%	20.8%	22.2%	21.4%	21.5%
Age 30-39	22.2%	23.2%	24.3%	21.9%	20.3%	18.0%	18.2%	18.8%
Age 50-64	29.7%	29.3%	26.1%	29.4%	30.6%	32.4%	34.0%	33.5%
African American	0.4%	0.1%	0.6%	0.7%	0.6%	1.0%	1.1%	0.7%
Other Race	1.3%	2.6%	1.1%	1.9%	1.3%	1.1%	1.0%	1.0%
Hispanic	0.6%	0.6%	0.6%	0.8%	0.9%	0.5%	0.6%	0.8%
Married	59.6%	58.2%	56.4%	55.8%	57.1%	58.3%	58.2%	57.2%
High School Drop-out	9.3%	8.4%	10.4%	10.1%	9.7%	9.2%	8.7%	6.6%
Some College	30.2%	26.9%	28.3%	27.6%	29.6%	31.0%	29.9%	29.2%
College Graduate	15.1%	16.3%	16.1%	16.9%	16.2%	17.2%	17.8%	18.2%
Worker	78.4%	78.5%	76.7%	73.7%	76.9%	75.4%	75.9%	76.9%
Firm size: Under 10	14.5%	16.7%	16.7%	19.7%	17.0%	18.7%	16.4%	16.3%
Firm size: 10 - 24	19.5%	16.9%	19.6%	19.4%	20.0%	18.9%	19.3%	20.5%
Firm size: 25 - 99	8.4%	8.3%	7.5%	7.6%	6.8%	7.3%	6.9%	7.4%
Firm size: 100 - 499	10.8%	10.6%	11.8%	12.1%	11.0%	11.6%	11.0%	10.1%
Firm size: 500 - 999	15.4%	14.8%	13.2%	11.9%	12.1%	13.3%	13.8%	14.1%
Firm size: 1000+	5.2%	5.9%	3.7%	4.3%	5.4%	4.4%	4.7%	4.5%

	2000	2001	2002	2003	2004	2005	2006	2007
Disabled	12.9%	12.2%	11.2%	12.8%	12.6%	11.4%	11.9%	13.0%
Medicaid Eligible	9.5%	10.1%	10.3%	10.7%	8.9%	10.9%	9.6%	9.7%
Schip Eligible	2.9%	2.7%	3.2%	3.3%	3.0%	3.4%	3.6%	2.9%
Up to 100%FPL	13.3%	14.1%	16.7%	15.3%	16.6%	17.2%	14.5%	16.7%
100-125%FPL	4.7%	4.8%	3.8%	4.6%	3.5%	4.1%	3.9%	3.3%
126-200%FPL	10.9%	11.5%	12.0%	13.8%	10.5%	12.3%	11.5%	11.2%
401%FPL+	37.2%	37.9%	35.1%	34.8%	37.0%	36.4%	39.2%	38.2%
Metropolitan Area	38.0%	36.6%	37.6%	37.5%	44.1%	49.1%	49.4%	51.4%
Sample Size	1,994	1,892	1,855	1,964	2,122	2,165	2,184	2,080
Population	789,264	794,349	794,175	797,607	821,886	856,323	836,498	821,624

Source: Tabulations from the 2000-2008 March Supplement to the Current Population Survey.
Notes: The data are restricted to persons under age 65 living in Maine and weighted with the person level weights.

To further explore these results, we estimated a probit model with uninsurance as the dependent variable and "Maine" as the key independent variable (Figure 10). This model shows that, controlling for other factors, the uninsurance rate in Maine was slightly lower than the national average. Overall, the uninsurance rate for Maine was 0.8% lower than other states – a difference that was statistically significant (z=2.4, p=.016).

Figure 10: Probit Regression of the Difference between Maine and Other States on the Level of Uninsurance

	dF/dx	Std. Err.	z	P>|z|	[95%	C.I.]
Maine	-0.008	0.003	-2.400	0.016	-0.014	-0.002
Female	-0.022	0.001	-25.940	0.000	-0.024	-0.020
Age 19-29	0.059	0.002	39.910	0.000	0.056	0.062
Age 30-39	0.047	0.002	33.540	0.000	0.045	0.050
Age 40-49	0.032	0.001	24.120	0.000	0.029	0.034
Caucasian	-0.044	0.001	-41.190	0.000	-0.046	-0.041
Married	0.020	0.003	6.920	0.000	0.014	0.026
Head of Household	-0.025	0.001	-28.750	0.000	-0.027	-0.023
Household Size	-0.076	0.003	-25.580	0.000	-0.082	-0.070
US Born	-0.075	0.001	-56.440	0.000	-0.078	-0.072
Number of Kids	0.054	0.003	17.300	0.000	0.047	0.060
Moved with Previous 12 Month	0.042	0.001	34.290	0.000	0.040	0.045

	dF/dx	Std. Err.	z	P>|z|	[95%	C.I.]
Less than High School Education	0.059	0.002	42.640	0.000	0.056	0.062
Some College	-0.020	0.001	-19.610	0.000	-0.022	-0.018
College Graduate	-0.044	0.001	-35.940	0.000	-0.046	-0.042
Employed	-0.030	0.003	-11.580	0.000	-0.035	-0.025
Firm Size, 1-9	0.030	0.003	10.080	0.000	0.024	0.036
Firm Size, 10-24	0.166	0.002	92.300	0.000	0.162	0.170
Firm Size, 25-99	0.120	0.002	60.430	0.000	0.115	0.125
Firm Size, 100-199	0.061	0.002	35.780	0.000	0.058	0.065
Firm Size, 200-399	0.024	0.002	14.550	0.000	0.021	0.028
Firm Size, 400-499	0.007	0.002	2.760	0.006	0.002	0.011
Self Employed	0.015	0.002	6.960	0.000	0.011	0.020
Government Employee	-0.044	0.001	-28.680	0.000	-0.047	-0.042
Union Job	-0.046	0.009	-4.340	0.000	-0.063	-0.029
Full Time Student	-0.094	0.001	-56.000	0.000	-0.096	-0.092
Disabled	-0.090	0.001	-64.770	0.000	-0.092	-0.088
Income, 100%-125% of FPL	-0.013	0.002	-6.640	0.000	-0.017	-0.009
Income, 125%-200% of FPL	-0.039	0.001	-28.470	0.000	-0.041	-0.036
Income, 200%-400% of FPL	-0.113	0.001	-90.280	0.000	-0.115	-0.111
Income Over 400% of FPL	-0.211	0.001	-135.500	0.000	-0.213	-0.208
Metropolitan Area	-0.010	0.001	-8.650	0.000	-0.012	-0.008
County Unemployment Rate	-0.048	0.021	-2.290	0.022	-0.089	-0.007
County, Percent Under FPL	0.198	0.008	24.120	0.000	0.182	0.214
County, Percent of Employers with Under 10 Workers	0.073	0.010	7.370	0.000	0.054	0.093
County, Percent of Employers with 10-24 Workers	0.108	0.018	6.130	0.000	0.073	0.142
County, Percent of Employers with 25-99 Workers	-0.038	0.017	-2.280	0.023	-0.070	-0.005
County, Percent of Employers with 100-499 Workers	-0.198	0.015	-13.080	0.000	-0.227	-0.168

Next, we estimated a probit model with uninsurance as the dependent variable and "Dirigo Year" as the key independent variable (Figure 11). This model shows that, controlling for other factors, the uninsurance rate was higher nationally during the years of the Dirigo intervention than in prior years. Overall, the uninsurance rate for Dirigo years was 0.5% higher than in pre-Dirigo years – a difference that was statistically significant (z=3.2, p=.001).

Figure 11: Probit Regression of the Difference in the Level of Uninsurance Nationally Pre and Post Dirigo

	dF/dx	Std. Err.	z	P>|z|	[95%	C.I.]
Dirigo Year	0.0052	0.0016	3.2900	0.0010	0.0021	0.0084
Female	-0.0220	0.0008	-25.9400	0.0000	-0.0237	-0.0203
Age 19-29	0.0592	0.0016	39.9300	0.0000	0.0560	0.0623
Age 30-39	0.0475	0.0015	33.5600	0.0000	0.0445	0.0504
Age 40-49	0.0318	0.0014	24.1400	0.0000	0.0291	0.0345
Caucasian	-0.0436	0.0011	-41.2200	0.0000	-0.0458	-0.0415
Married	0.0201	0.0029	6.9300	0.0000	0.0145	0.0257
Head of Household	-0.0252	0.0009	-28.7400	0.0000	-0.0269	-0.0235
Household Size	-0.0760	0.0030	-25.5800	0.0000	-0.0819	-0.0702
US Born	-0.0749	0.0015	-56.4400	0.0000	-0.0778	-0.0720
Number of Kids	0.0535	0.0031	17.3000	0.0000	0.0474	0.0596
Moved with Previous 12 Month	0.0423	0.0013	34.2600	0.0000	0.0397	0.0449
Less than High School Education	0.0588	0.0015	42.6200	0.0000	0.0558	0.0618
Some College	-0.0201	0.0010	-19.6200	0.0000	-0.0220	-0.0181
College Graduate	-0.0438	0.0011	-35.9300	0.0000	-0.0460	-0.0417
Employed	-0.0299	0.0027	-11.5700	0.0000	-0.0352	-0.0246
Firm Size, 1-10	0.0303	0.0031	10.1100	0.0000	0.0241	0.0365
Firm Size, 11-49	0.1661	0.0021	92.3100	0.0000	0.1619	0.1703
Firm Size, 50-99	0.1200	0.0024	60.4300	0.0000	0.1154	0.1246
Firm Size, 100-199	0.0613	0.0019	35.7800	0.0000	0.0576	0.0650
Firm Size, 200-399	0.0241	0.0017	14.5600	0.0000	0.0207	0.0275
Firm Size, 400-499	0.0066	0.0024	2.7500	0.0060	0.0018	0.0113
Self Employed	0.0152	0.0023	6.9600	0.0000	0.0108	0.0196
Government Employee	-0.0443	0.0014	-28.6800	0.0000	-0.0469	-0.0416
Union Job	-0.0459	0.0088	-4.3400	0.0000	-0.0632	-0.0286
Full Time Student	-0.0939	0.0010	-55.9900	0.0000	-0.0959	-0.0920
Disabled	-0.0903	0.0010	-64.8100	0.0000	-0.0922	-0.0885
Income, 100%-125% of FPL	-0.0129	0.0019	-6.6500	0.0000	-0.0165	-0.0092
Income, 125%-200% of FPL	-0.0389	0.0012	-28.4900	0.0000	-0.0413	-0.0365
Income, 200%-400% of FPL	-0.1133	0.0011	-90.2800	0.0000	-0.1155	-0.1111
Income Over 400% of FPL	-0.2106	0.0015	-135.5100	0.0000	-0.2134	-0.2077
Metropolitan Area	-0.0097	0.0011	-8.6100	0.0000	-0.0119	-0.0075
County Unemployment Rate	-0.0334	0.0214	-1.5600	0.1180	-0.0753	0.0085

	dF/dx	Std. Err.	z	P>|z|	[95%	C.I.]
County, Percent Under FPL	0.1973	0.0082	24.0100	0.0000	0.1811	0.2134
County, Percent of Employers with Under 10 Workers	0.0749	0.0099	7.5400	0.0000	0.0554	0.0943
County, Percent of Employers with 10-24 Workers	0.1096	0.0176	6.2300	0.0000	0.0752	0.1441
County, Percent of Employers with 25-99 Workers	-0.0395	0.0166	-2.3800	0.0170	-0.0720	-0.0070
County, Percent of Employers with 100-499 Workers	-0.1993	0.0151	-13.2300	0.0000	-0.2289	-0.1698
Year	0.0008	0.0003	2.5200	0.0120	0.0002	0.0013

These two results suggest that the difference in difference model is necessary to find the true Dirigo effect. Maine had lower average uninsurance rates than other states and national uninsurance rates in Dirigo years were higher than in other years. But the full model that controls for both of these effects and looks at whether the difference between Maine and the rest of the country changed during the Dirigo years is the difference in difference model, and is described below.

B. Analytic Results: Non-Medicaid/SCHIP/Medicare Eligible Adults Difference in Difference

To control for changes in the underlying variables, we estimated a logit regression model with fixed effects for states, as described previously. The results of that analysis are presented in Figure 12. The analysis in Figure 12 includes adults between the ages of 19 and 64 who are not eligible for SCHIP or Medicaid (or age eligible for Medicare). The first coefficient, “Maine”, shows the average difference between Maine and all other states during the entire time period (2000-2007). During that time, the uninsurance rate in Maine was statistically insignificantly different from other states, controlling for other factors (p=.56). The second coefficient shows the average difference between the Dirigo years (2005-2007) for all states; on average, the uninsurance rate was 0.5% higher during Dirigo years than non-Dirigo years across the entire country. This difference is statistically significant (p=.001).

The third coefficient, labeled “Dirigo Effect” shows the difference in difference – that is, differential changes in the difference between Maine and the rest of the country during the Dirigo years. That shows that in this population, controlling for other factors, Dirigo lowered the rate of uninsurance in Maine by 1.94% in adults between the ages of 19 and 64 who are not eligible for SCHIP or Medicaid (or age eligible for Medicare). This difference is statistically significant, with a z statistic of -3.63 and a p value of less than 0.0001. Thus, the Dirigo initiative significantly reduced the rate of uninsurance in the non-Medicaid/SCHIP/Medicare eligible population.

Figure 12: Effect of Dirigo Intervention on the Rate of Uninsurance in Maine

	dy/dx	Std. Err	z	P>|z|	[95%	C.I.]
Maine	-0.0027	0.0047	-0.5800	0.5630	-0.0119	0.0065
Dirigo Year	0.0049	0.0014	3.4100	0.0010	0.0021	0.0077
Dirigo Effect: Difference in Difference	-0.0194	0.0054	-3.6300	0.0000	-0.0299	-0.0089
Female	-0.0206	0.0008	-27.1500	0.0000	-0.0221	-0.0191
Age 19-29	0.0523	0.0015	35.1700	0.0000	0.0494	0.0552
Age 30-39	0.0452	0.0014	31.9200	0.0000	0.0424	0.0479
Age 40-49	0.0302	0.0013	23.7400	0.0000	0.0277	0.0327
Caucasian	-0.0350	0.0010	-34.4500	0.0000	-0.0369	-0.0330
Married	0.0144	0.0025	5.8400	0.0000	0.0095	0.0192
Head of Household	-0.0223	0.0008	-28.1800	0.0000	-0.0239	-0.0208
Household Size	-0.0666	0.0026	-26.0400	0.0000	-0.0716	-0.0616
US Born	-0.0708	0.0014	-49.1300	0.0000	-0.0736	-0.0679
Number of Kids	0.0457	0.0027	17.0900	0.0000	0.0404	0.0509
Moved with Previous 12 Month	0.0351	0.0012	29.4200	0.0000	0.0328	0.0375
Less than High School Education	0.0461	0.0014	33.9900	0.0000	0.0435	0.0488
Some College	-0.0191	0.0009	-21.4600	0.0000	-0.0208	-0.0174
College Graduate	-0.0395	0.0010	-39.3600	0.0000	-0.0414	-0.0375
Employed	-0.0263	0.0025	-10.7200	0.0000	-0.0311	-0.0215
Firm Size, 1-10	0.0287	0.0029	9.9100	0.0000	0.0230	0.0344
Firm Size, 11-49	0.1573	0.0022	71.6500	0.0000	0.1530	0.1616
Firm Size, 50-99	0.1132	0.0024	48.1000	0.0000	0.1086	0.1179
Firm Size, 100-199	0.0568	0.0018	31.1000	0.0000	0.0532	0.0603
Firm Size, 200-399	0.0222	0.0016	13.5900	0.0000	0.0190	0.0254
Firm Size, 400-499	0.0067	0.0023	2.9200	0.0030	0.0022	0.0111
Self Employed	0.0149	0.0021	7.1800	0.0000	0.0109	0.0190
Government Employee	-0.0428	0.0012	-34.8100	0.0000	-0.0452	-0.0404
Union Job	-0.0408	0.0079	-5.1400	0.0000	-0.0563	-0.0252
Full Time Student	-0.0793	0.0009	-89.4500	0.0000	-0.0810	-0.0775
Disabled	-0.0799	0.0008	-98.2000	0.0000	-0.0815	-0.0783
Income, 100%-125% of FPL	-0.0109	0.0016	-6.9500	0.0000	-0.0139	-0.0078
Income, 125%-200% of FPL	-0.0325	0.0010	-31.3500	0.0000	-0.0346	-0.0305
Income, 200%-400% of FPL	-0.0954	0.0010	-97.0000	0.0000	-0.0973	-0.0934
Income Over 400% of FPL	-0.1929	0.0014	-134.530	0.0000	-0.1957	-0.1901
Metropolitan Area	-0.0082	0.0011	-7.4100	0.0000	-0.0104	-0.0060
County Unemployment Rate	0.0691	0.0202	3.4200	0.0010	0.0295	0.1086
County, Percent Under FPL	0.0918	0.0088	10.4100	0.0000	0.0745	0.1091

	dy/dx	Std. Err	z	P>|z|	[95%	C.I.]
County, Percent of Employers with Under 10 Workers	0.0640	0.0105	6.0900	0.0000	0.0434	0.0846
County, Percent of Employers with 10-24 Workers	0.0856	0.0162	5.2800	0.0000	0.0538	0.1173
County, Percent of Employers with 25-99 Workers	0.0431	0.0155	2.7700	0.0060	0.0126	0.0736
County, Percent of Employers with 100-499 Workers	0.0028	0.0151	0.1900	0.8500	-0.0267	0.0324
Year	0.0008	0.0003	3.1600	0.0020	0.0003	0.0014

We estimated these models using a number of different specifications to ensure the robustness of our results. We include our preferred model in the first row below in Figure 13, accompanied by estimates using both logit and probit specifications with and without fixed effects corrections. In all models, the estimated effects were similar, ranging from a low of 1.82% reduction in uninsurance to a high of a 2.07% reduction in uninsurance. In all cases, the models were statistically significant.

Figure 13: Effect of Dirigo on the Marginal Probability of Uninsurance using Different Specifications

Model	Estimated Marginal Effect	Standard Error	Test statistic	P value	95% Confidence Interval
Logit with Fixed Effects	-0.0194	0.0054	-3.63	<0.0000	-0.0299 to -0.0089
Probit, No Fixed Effects	-0.0195	0.0061	-3.00	0.003	-0.0315 to -0.0075
Logit, No Fixed Effects	-0.0183	0.0055	-3.33	0.001	-0.0290 to -0.0075
Probit, Fixed Effects	-0.0207	0.0060	-3.23	0.001	-0.0325 to -0.0089

Using the estimates from the fixed effects logit, we can project the effect of Dirigo on the number of uninsured among non-Medicaid, SCHIP (and Medicare age) eligible adults, age 19-64 (Figure 14). Among this population, the actual uninsured rate varied between 11.8% and 13.6%. Following the enactment of Dirigo, it declined by 1% in Year 1 (2005) and then a further 1.8% for 2006, before holding relatively steady in 2007. During the first year of Dirigo, the number of uninsured in this population declined by approximately 9,400 from 2004 to 2005 and a further 13,000 the following year before holding relatively steady the next year. We project that if Dirigo had not been enacted, the uninsurance rate would have been 1.9% higher in each year, or approximately 13,103 (3 year average) additional individuals would have been uninsured in the absence of the program.

Figure 14: Projected Number of Non Medicaid-SCHIP Eligible Adults Age 19-64 Without Health Insurance With and Without Dirigo

Year	Population	Estimated Uninsured Rate	Projected Uninsured Rate Without Dirigo	Estimated Uninsured	Projected Uninsured Without Dirigo	Difference
2000	712,871	11.8		84,119		
2001	713,678	11.7		83,500		
2002	709,401	12.7		90,094		
2003	711,872	13.6		96,815		
2004	746,630	12.8		95,569		
2005	730,266	11.8	13.7%	86,171	99,316	13,145
2006	730,440	10.0	11.9%	73,044	86,192	13,148
2007	723,081	10.1	12.0%	73,031	86,047	13,015
3 Year Average 2005-2007						13,103

C. Analytic Results: Non-Medicaid/SCHIP Eligible Children

This section of the analysis focuses on children under age 19 who are not eligible for either SCHIP or Medicaid. The model is similar to that of the adults except that several of the variables reflect attributes of the head of the household. For example, variables indicating educational achievement (e.g., college graduate, high school graduate) are inappropriate for children, as these variables reflect parents' educational attainment.

We found no evidence that Dirigo decreased the rate of uninsurance among children (Figure 15). The estimated Dirigo effect was insignificantly different from zero (p=0.53). Overall, Maine had a significantly higher uninsurance rate than other states after controlling for other factors – overall, the uninsurance rate among children was 1.33% higher (p=0.04).

Figure 15: Effect of Dirigo Intervention on the Rate of Uninsurance in Maine Among Children

	dy/dx	Std. Err	z	P>|z|	[95%	C.I.]
Maine	0.0133	0.0066	2.0200	0.0440	0.0004	0.0262
Dirigo Year	0.0091	0.0015	6.1300	0.0000	0.0062	0.0120
Dirigo Effect: Difference in Difference	-0.0031	0.0050	-0.6300	0.5290	-0.0129	0.0066
Female	0.0002	0.0007	0.3400	0.7320	-0.0011	0.0016
Age Under 1	-0.0130	0.0246	-0.5300	0.5960	-0.0612	0.0351
Age 1-5	-0.0097	0.0011	-9.0700	0.0000	-0.0118	-0.0076
Age 6-16	-0.0070	0.0011	-6.3900	0.0000	-0.0092	-0.0049

	dy/dx	Std. Err	z	P>|z|	[95%	C.I.]
Caucasian	-0.0273	0.0011	-24.0000	0.0000	-0.0295	-0.0250
Household Size	-0.0106	0.0036	-2.9700	0.0030	-0.0176	-0.0036
US Born	-0.0366	0.0029	-12.6300	0.0000	-0.0423	-0.0310
Number of Kids	0.0086	0.0036	2.3800	0.0170	0.0015	0.0157
Moved within Previous 12 Months	0.0096	0.0014	7.1000	0.0000	0.0070	0.0123
Household Head Married	0.0035	0.0034	1.0500	0.2920	-0.0030	0.0101
Household Head High School Graduate	0.0140	0.0014	10.2900	0.0000	0.0114	0.0167
Household Head Some College	-0.0001	0.0010	-0.1300	0.8940	-0.0022	0.0019
Household Head College Graduate	-0.0114	0.0010	-11.7900	0.0000	-0.0133	-0.0095
Household Head Employed	-0.0243	0.0025	-9.8300	0.0000	-0.0291	-0.0194
Household Head Disabled	-0.0018	0.0016	-1.1300	0.2590	-0.0049	0.0013
Household Head Firm Size, 1-10	0.0443	0.0083	5.3500	0.0000	0.0281	0.0606
Household Head Firm Size, 11-49	0.1105	0.0033	33.3700	0.0000	0.1040	0.1170
Household Head Firm Size, 50-99	0.0841	0.0034	24.7300	0.0000	0.0774	0.0907
Household Head Firm Size, 100-199	0.0489	0.0023	21.7300	0.0000	0.0444	0.0533
Household Head Firm Size, 200-399	0.0248	0.0017	14.6000	0.0000	0.0215	0.0282
Household Head Firm Size, 400-499	0.0088	0.0021	4.1800	0.0000	0.0047	0.0129
Income, 125%-200% of FPL	0.0346	0.0206	1.6800	0.0930	-0.0058	0.0750
Income, 200%-400% of FPL	-0.0124	0.0023	-5.3600	0.0000	-0.0170	-0.0079
Income Over 400% of FPL	-0.0336	0.0028	-12.0000	0.0000	-0.0391	-0.0281
Metropolitan Area	-0.0062	0.0011	-5.8000	0.0000	-0.0083	-0.0041
County Unemployment Rate	0.0030	0.0197	0.1500	0.8790	-0.0356	0.0417
County, Percent Under FPL	0.0554	0.0086	6.4200	0.0000	0.0385	0.0723

	dy/dx	Std. Err	z	P>|z|	[95%	C.I.]
County, Percent of Employers with Under 10 Workers	0.0142	0.0098	1.4500	0.1480	-0.0050	0.0334
County, Percent of Employers with 10-24 Workers	0.0200	0.0158	1.2700	0.2040	-0.0109	0.0509
County, Percent of Employers with 25-99 Workers	0.0017	0.0145	0.1200	0.9070	-0.0267	0.0301
County, Percent of Employers with 100-499 Workers	0.0381	0.0141	2.7100	0.0070	0.0105	0.0657
Year	-0.0017	0.0003	-6.3300	0.0000	-0.0022	-0.0011

D. Uncompensated Care Pre- and Post-Dirigo

Pre- and Post-Dirigo burden of uncompensated care in Maine is projected by applying per capita growth in health care expenditures[35] to the 2005 estimates of uncompensated care per uninsured as presented in Thorpe (2005). It should be noted that using the national health spending growth as an inflationary factor to project uncompensated care likely results in an overstatement of the total burden of uncompensated care in the State. Regulations in the private insurance market introduced throughout the 1990's ("modified community rating" and "guaranteed renewal") along with cost containment efforts under the Dirigo reform including greater regulation of "premium rates", introduction of rate review by the Bureau of Insurance, and DirigoChoice benefits (coverage of pre-existing conditions, no lifetime benefit caps, etc.) are likely to have constrained inflation in the health care in the State over the period[36,37]. At the same time, the uninsured face higher inflationary pressures than those with health coverage[38]

[35] National Health Accounts, Department of Health and Human Services, Centers for Medicaid and Medicare: http://www.cms.hhs.gov/NationalHealthExpendData/downloads/proj2007.pdf (accessed on October 28, 2009)
[36] "Maine's Dirigo Health Reform of 2003," State Expansions, Families USA, November 2007: http://www.familiesusa.org/assets/pdfs/state-expansions-me.pdf (accessed on October 28, 2009);
[37] Suacier, P., "MaineCare and its Role in Maine's Healthcare System," report to Kaiser Commission on Medicaid and the Uninsured from Muskie School of Public Service, January 2005: http://www.kff.org/medicaid/upload/MaineCare-and-Its-Role-in-Maine-s-Healthcare-System-Report.pdf
[38] For instance, Anderson, "From 'Soak The Rich' To 'Soak The Poor': Recent Trends In Hospital Pricing" (2007) provides evidence showing that the uninsured are paying an increasingly higher rate for hospital services relative to those with health insurance coverage, on average facing over 2.5 times higher hospital bills than the insured.

and are thus likely to experience annual increases in health costs at above the national rate, potentially understating the increase in uncompensated care over the period.

Estimates of uncompensated care in Maine were derived from uncompensated care projections presented in Thorpe (2005). Maine totals for 2005 were divided by the estimates of the number of uninsured to obtain per capita figure for the full population. Estimates of the mean uncompensated care per uninsured elderly persons and uninsured non-elderly were computed by applying the methodology developed in Thorpe (2005) to 2002 MEPS data.

On average, we estimated that the mean per capita cost for an uninsured person for bad debt and charity care in 2008 was $893[39]. This suggests that the Dirigo initiative reduced costs associated with Bad debt and charity care by approximately $893 for each of the 13,015 individuals who gained insurance due to Dirigo, for a total net savings of $11,622,395.

It should be noted that the BD/CC savings calculation does not account for new utilization by the previously uninsured. The formula only looks at existing levels of service utilization by the previously uninsured. There is not data at this time to quantify additional savings due to additional insurance reimbursement in the system. As a result, we have not quantified associated additional savings.

Conclusions

Since the enactment of the Dirigo Health Reform Act, there was a reduction in the rate of uninsurance among the non-elderly in the Maine. Had Dirigo not been enacted, an additional 13,015 non-elderly Maine residents would have lacked health coverage in 2008, a figure we held steady from 2007 for the purposes of this analysis. Expansions in access to health insurance from 2005 to 2008 directly affected the burden of uncompensated care in the State, potentially contributing to reductions in premium inflation and easing outlays to cover the bad debt and charity care incurred by the uninsured. We estimate that decreases in uninsurance prevalence due to the Dirigo Act yielded cost savings in 2008 of $11.6 million uncompensated care. It is important to note, however, that cost efficiencies realized in the health care system through the Dirigo initiatives are not fully captured by these simulations since we are only reviewing one of the Dirigo reform initiatives: the decreasing burden of uncompensated care through the reduction in the number of uninsured in the State.

[39] File containing calculations and assumptions can be found in documentation: Uncompensated Care Calc.xls

3. YEAR 4 AMCS CALCULATIONS – CMAD

A major part of the Dirigo reforms focused on restraining the key cost drivers in the Maine health care marketplace. Maine, to restrain costs in the past, had regulated certain portions of the health care marketplace, including hospital reimbursement using vehicles like the Maine Health Care Financing Commission. During the debate over Dirigo, the Maine hospitals argued that mandatory cost restraints were not necessary and that they would adhere to Dirigo's voluntary targets. As a result of adhering to the targets, the hospitals argued, the resulting reductions in the rate of growth of hospital expenditures would provide the State with the reductions needed to make health insurance more affordable in Maine. This section of the report focuses on the effect of the voluntary targets on actual observed spending with the Dirigo health reform and projected spending in the absence of Dirigo. The description that follows relies primarily on Medicare Cost Reports (MCRs) to estimate the effect of Dirigo on the rate of growth in hospital costs in Maine.

The evaluation examines the following questions:

1. Is there a statistically significant relationship between the implementation of Dirigo and the rate of growth in hospital costs in Maine?
2. If so, is the relationship positive or negative? A positive relationship would indicate that Dirigo had increased the rate of hospital cost growth in Maine and a negative relationship would indicate that Dirigo had reduced the rate of hospital cost growth in Maine.
3. What is the statistical strength of the relationship?

If the relationship is negative, we then use the volume adjusted discharges (case-mix adjusted hospital inpatient discharges and a proxy using revenue ratios to approximate hospital outpatient volume) combined with the reduction in cost per case-mix adjusted discharge (CMAD) to provide an estimate of the reduction in cost for health care expenditures in Maine associated with Dirigo.

In this section, we have described the detailed approach to calculating the Year 4 CMAD AMCS. We have organized the section into the following:

- Background
- Data Sources and Collection
- Data Compilation and Calculations
- Methods
- Conclusions

BACKGROUND

Maine has used a variety of approaches to control health care costs in the past. The Maine Health Care Finance Commission regulated hospital costs in Maine from approximately 1983 to 1995. Included in the legislative debate over Dirigo was a discussion to return to direct regulatory oversight of hospital costs, included mandatory limits on cost increases and operating margins. The Maine hospitals and their trade group, the Maine Hospital Association (MHA), argued that such direct regulatory oversight on hospital costs was not necessary and successfully lobbied instead for voluntary targets to restrain hospital costs.

In lieu of formal regulation, the Maine hospitals agreed to voluntary targets for cost increases and operating margin. For limiting future hospital cost increases, the hospitals and MHA agreed to use a standardized measure of hospital costs, namely CMAD. CMAD is the amount of money it costs for a patient to receive care during an inpatient hospital stay or outpatient service encounter. The case-mix adjustment takes into account different types of patients and treatments (discharges) that require different levels of effort and cost in the inpatient setting. As there is no true discharge associated with outpatient services, outpatient services provided at a hospital are factored in through a volume-adjusted revenue ratio meant to proxy the impact of outpatient volume on total hospital costs.

As noted in AMCS proceedings for Years 1-3, there are positive effects due to hospitals holding down the rate of growth in their CMAD. The dominant approach to hospital reimbursement in Maine can be characterized as "discount off charges". Effectively, hospitals in Maine must look at their projected costs and determine the level of charges and associated discounts that generate sufficient revenue for that hospital fiscal year. Thus, reductions in the projected costs due to lower rates of cost growth result in lower rates of growth for hospitals' charges and/or reimbursement rates paid by those insured or those who pay for services directly. Lower CMAD trends over time result in lower charges or lower premiums paid by the consumers, resulting in savings to the Maine health care system.

In past years' proceedings, Dirigo has presented evidence demonstrating that the MHA and the Maine hospitals themselves have made substantial efforts to reduce the rate of cost growth:

Figure 16: Statements from MHA and Hospital Representatives Concerning Adhering to Dirigo's Voluntary Cost-Control Targets

Source	Position	Summary of Evidence
Maine Hospital Association (MHA)[40]	Association of all hospitals in Maine	Maine hospitals are in support of and adhering to the limits set for by the Dirigo Reform Act and will continue to do so.
Steve Michaud[41,42]	President, Maine Hospital Association	Dirigo savings have resulted from hospitals adhering to the voluntary cost limits and those savings have been passed on to the insurers. The hospitals will continue to adhere to the voluntary targets.
Elizabeth Mitchell[43]	Senior Director of Public Policy at MaineHealth	There is plentiful evidence that the voluntary CMAD efforts that began four years ago are one aspect of the Dirigo reforms that are working. Maine Medical Center has reduced its prices four times during the past three years, saving almost $40 million.
Mary Mayhew[44,45]	Vice President, Maine Hospital Association	Hospitals are adhering to the voluntary CMAD targets for three years in a row with more than $50 million being saved as a result of the voluntary caps.
Ralph Gabarro[46]	CEO of Mayo Regional Hospital	Mayo Regional Hospital is in support of the Dirigo Reform Act and adheres to the cost and operating limits within it.

In addition to the hospitals' direct efforts to reduce CMAD growth, there are other aspects of the Dirigo reform that directly or indirectly affect CMAD. The greatly strengthened Certificate of Need (CON) process and newly implemented Capital Investment Fund (CIF) are Dirigo initiatives monitoring and limiting provider capital investments and expansions. These limits and

[40] Maine Hospital Association, "Pointing the way" (2005)
[41] Memorandum from Steve Michaud, re: Testimony in Opposition to LD 1935 - An Act to Protect Health Insurance Consumers (2/14/2006)
[42] Maine Hospital Association Release, "Maine hospitals do their part: Hospitals Volunteer to Cap Costs for another Year" (2004)
[43] Elizabeth Mitchell, "A booster shot, and more, for health care" Portland Press Herald (2008)
[44] Mary Mayhew, "Divided Hospital Study Commission unable to agree on final report" (2005)
[45] Mary Mayhew, "Testimony in Opposition to LD 1849, An Act To Protect Consumers from Rising Health Care Costs" (2007)
[46] Ralph Gabarro, "Testimony presented by Ralph Gabarro, CEO Mayo Regional Hospital, Dover-Foxcroft on behalf of the Maine Hospital Association" (2005)

monitoring activities also contribute to a lower CMAD now with Dirigo than would have been in the absence of Dirigo.

One approach to estimating the direct effect of Dirigo on the rate of cost growth in Maine's hospitals would be to simply compare the rates of cost growth prior to Dirigo and substituent to the reform. This, however, could misstate the impact of Dirigo on average CMAD costs because average costs after Dirigo could be affected by other factors, such as changes in technology or reimbursement rules that would have changed average CMAD values even in the absence of the Dirigo reform. It is thus necessary to both control for important factors that impact average CMAD values that are specific to Maine that may have changed after Dirigo and also to have a control group – which is necessarily not from Maine – to compare changes in costs pre and post Dirigo. We can develop an effective control group using national experience. The national control group provides good estimates of the experience of hospitals like those in the treatment group in the absence of Dirigo. Completely addressing the comparability of the treatment and control groups on unobservable variables would require an instrumental variable or selectivity estimation approach, which was not available for this evaluation. However, we did employ both random and fixed effects models (discussed in more detail below) to control to some extent for unobserved variables.

It is important to note that this analysis does not hypothesize either that Dirigo reduces CMAD either in absolute terms or relative to national or regional averages. It merely hypothesizes that Dirigo reduces CMAD *below what they would have been in Maine without Dirigo*. This counterfactual – average CMAD in Maine in the absence of Dirigo – cannot be directly observed. Instead, we will use statistical models to estimate likely values.

DATA SOURCES AND COLLECTION

Appendix C provides a summary of all the steps taken to collect data, compile them, and then analyze resulting datasets to calculate CMAD savings. These steps are described in detail here.

In Figure 17 below, we provide a listing of the many different publicly available and transparent data sources used to determine the appropriate savings estimate for the Hospital Savings Initiative (CMAD).

Figure 17: CMAD Data Sources

Data	Time Period	Source - Links accessed –October 28, 2009
Medicare Cost Reports		Centers for Medicare and Medicaid Services[47]: http://www.cms.hhs.gov/CostReports/CostReportsFY/list.asp#TopOfPage

[47] Individual Years' data hyperlinks are no longer available through CMS. The original data used to develop this report has been updated, resulting in a replacement of the original links used by CMS. Please refer to the documentation package as laid out in the subsequent cells for the source data used to develop this report.

Data	**Time Period**	**Source - Links accessed –October 28, 2009**
	Hospital Fiscal Year 1998	Refer to Data Documentation: Raw Data\Hospital2009_03_31FY1998.zip
	Hospital Fiscal Year 1999	Refer to Data Documentation: Raw Data\Hospital2009_03_31FY1999.zip
	Hospital Fiscal Year 2000	Refer to Data Documentation: Raw Data\Hospital2009_03_31FY2000.zip
	Hospital Fiscal Year 2001	Refer to Data Documentation: Raw Data\Hospital2009_03_31FY2001.zip
	Hospital Fiscal Year 2002	Refer to Data Documentation: Raw Data\Hospital2009_03_31FY2002.zip
	Hospital Fiscal Year 2003	Refer to Data Documentation: Raw Data\Hospital2009_03_31FY2003.zip
	Hospital Fiscal Year 2004	Refer to Data Documentation: Raw Data\Hospital2009_03_31FY2004.zip
	Hospital Fiscal Year 2005	Refer to Data Documentation: Raw Data\Hospital2009_03_31FY2005.zip
	Hospital Fiscal Year 2006	Refer to Data Documentation: Raw Data\Hospital2009_03_31FY2006.zip
	Hospital Fiscal Year 2007	Refer to Data Documentation: Raw Data\Hospital2009_03_31FY2007.zip
	Hospital Fiscal Year 2008	Refer to Data Documentation: Hospital2009_03_31FY2008.zip
Provider ID Lookup	All Years	Centers for Medicare and Medicaid Services: Refer to Data Documentation: Raw Data\HOSPITALPROVIDERID1208.zip
Medicare Payor Case-Mix Index	Hospital Fiscal Years (HFYs)	American Hospital Database calculation using Medicare Provider Analysis and Review (MEDPAR) file Refer to: MCR Data_Raw.txt and sschramm080417_cmi.txt
Healthcare Cost & Utilization Project (HCUP) Discharge Data	CYs 2001 - 2004	Compiled using HCUP SID Database: http://hcupnet.ahrq.gov/HCUPnet.jsp?Id=8EFC8EED51FE5D7E&Form=MAINSEL&JS=Y&Action=%3E%3ENext%3E%3E&_MAINSEL=State%20Statistics Refer to ALLPAYOR CONVERSION.xls
Diagnosis Related Group (DRG) Weights	FFYs 2001 - 2004	Centers for Medicare and Medicaid Services: http://www.cms.hhs.gov/AcuteInpatientPPS/downloads/hist_drg_1500f.zip
Hospital Zip Code Data	Snapshot as of February 2009	Zip Code Download website: http://www.zipcodedownload.com Refer to 5-digit Commercial.csv
Critical Access Hospital Information	N/A	Compiled by Flex Monitoring Team: http://www.flexmonitoring.org/cahlistRA.cgi Refer to: CAH List with IDs.xls
FIPS Code Conversion: State	N/A	U.S. Census Bureau: http://www.census.gov/geo/www/ansi/statetables.html
Hospital Provider Tax	SFYs 2004 - 2007	Received from State of Maine - refer to: Final-Tax-@ .74% 3-16-04 A.xls Tax SFY 2005.xls Tax SFY 2006.xls Tax amounts 3.41 SFY 2007.xls

- **Medicare Cost Reports**

  The Medicare Cost Reports (MCRs) contain the bulk of the hospital-specific information used during the calculations. In preparation for the Year 4 CMAD calculation, **srHS** researched alternate sources for the MCR information. In order to have the most transparent data collection process possible, **srHS** opted for the very intensive process of compiling the MCR information as posted directly on the Centers for Medicare and Medicaid Services (CMS) website. By compiling the data directly from CMS, **srHS** was able to monitor every facet of the data entering the calculation. See Appendix D for a sample audit performed by **srHS**. A detailed data log was created to document every step from downloading the data to calculating the resulting savings amount. This data log can be seen in SAS Code Descriptions.xls in the documentation package. As mentioned previously, a summary of this can be seen within Appendix C. Also, the data refinements and calculation changes across AMCS years are shown in Appendix E.

- **Supplementary Hospital Information**

  CMS provides supplementary files to use in conjunction with the hospital cost report data. These files provide additional information on each hospital that files a cost report. **srHS** used this information to add the zip code for each hospital to the compiled MCR record. The zip code is reported on the hospital's MCR, but after reviewing the consistency of the data, it was determined that the supplementary hospital information from CMS was a more thorough data source than the actual cost report field for this data.

- **Case-Mix Index**

  The cost report filed annually by each hospital does not include the Case-Mix Index (CMI). CMS does provide supplementary files that list this information for some hospitals, but this only covers the hospitals that are subject to the Inpatient Prospective Payments System (IPPS). In order to receive this information for hospitals subject to Cost-Based Reimbursement, e.g. critical access hospitals, a different source for the information was needed. **srHS** received the Medicare CMI for each hospital in the country from the American Hospital Directory (AHD). This is a figure that AHD calculated using the Medicare Provider Analysis and Review (MEDPAR) File to create a composite index for the relative risk of each hospital's Medicare population.

- **All-Payor Discharge Information**

  The statutory formula for calculating the CMAD value specifies that an all-payor CMI be used within the calculation. To compute an all-payor CMI, **srHS** used a methodology which involved downloading discharge information from the Healthcare Cost & Utilization Project (HCUP) for all diagnosis-related groups (DRGs) across multiple states and years for both Medicare payors as well as All-payors. The State Inpatient Database (SID) was used to procure this information. It was then used in conjunction with case weights for each of the

DRGs from CMS in order to compute a composite index for the relative risk of each state's Medicare population versus an all-payor composite. **srHS** looked at this ratio across the multiple states and years to develop the adjustment factor which it would then apply to the Medicare CMI for each hospital for each year.

- **Regional FIPS Code**

In order to group the hospitals into common regions, **srHS** purchased a crosswalk from http://www.zipcodedownload.com which was used to assign a County FIPS identifier to each hospital record by using the known zip code. **srHS** could not find a comparable, publicly available crosswalk. Those records with unknown zip codes were given a State FIPS identifier. This process allowed for the additional county-level CPS regression variables to be added to the hospital data.

- **Critical Access Hospital Information**

srHS contacted the US Department of Health and Human Services' (DHHS') Flex Monitoring Team in order to gain information on when hospitals convert to critical access status. The DHHS Flex Monitoring Team is made up of researchers from the Universities of Minnesota, North Carolina at Chapel Hill, and Southern Maine under contract to the Federal government. They are the recipients of an agreement award from the Federal Office of Rural Health Policy to monitor the Medicare Rural Hospital Flexibility Grant Program. The researchers have a publicly available data set on their website at: http://www.flexmonitoring.org/documents/CAH_LIST_01_26_09.xls. The version on their website did not contain the hospital provider number. **srHS** contacted the Flex Monitoring Team who then provided an updated version[48] of the same worksheet which contained the provider numbers. This information was then used to create an indicator within the hospital cost report data set indicating the critical access status of the hospital.

- **Hospital Provider Tax**

Starting in 2004, hospitals in Maine were subject to an annual provider tax equal to a percentage of total hospital net patient service revenue (gross revenue less charity care and contractuals). Per statutory guidelines set forth in determining how to calculate the value for each hospital's CMAD, the amount of this tax was removed from the costs reported on the hospital's cost report. Because this tax is not parsed out specifically on a MCR, **srHS** relied on Maine Health Data Organization (MHDO) to furnish the actual tax amounts levied on each of the hospitals for SFYs 2004 – 2007. These amounts can be seen in the following files: Final-Tax-@ .74% 3-16-04 A.xls, Tax SFY 2005.xls, Tax SFY 2006.xls, and Tax amounts 3.41 SFY 2007.xls.

[48] Refer to: CAH List with IDs.xls

- **County Level Variables**

  We also used data from the Area Resource File (ARF) for several county level variables that were used to check our model specifications. The ARF is collected by the Health Resources and Services Administration (HRSA) and is designed to be used by planners, policymakers, researchers, and others interested in the nation's health care delivery system and factors that may impact health status and health care in the U.S. HRSA collects data from other public sources, such as the Census Bureau, and compiles it into yearly data.

At the time **srHS** completed this analysis (analysis conducted in the first and second quarters of calendar year 2009) for CMAD, **srHS** used the most recent data available at that time. For example, as noted above, the primary source of data for CMAD are the MCRs and **srHS** used the most recent MCRs data available as of March 31, 2009. CMS continually updates MCR data as it is received from the hospitals. We have not incorporated any updated MCR data beyond March 31, 2009 in to our analysis as of the time of this report. We have included a link to the updated MCRs[49] as part of the documentation for this report.

DATA COMPILATION AND CALCULATIONS

Data Quality Control

Any time large amounts of data are compiled across multiple sources, it is customary to run standard checks of validity. The raw data processed and used to calculate the CMAD savings went through multiple checks and controls to ensure that anomalous data was removed and no additional data was created as a byproduct of processing. **srHS** grouped the fields of its master data set into two main groups: those variables and values necessary at the calculation level versus those variables and values necessary at the regression level. Different steps were taken to ensure that each group was tested both appropriately and thoroughly.

- **Calculation Level Data**

  Calculation level data is defined as the information necessary to calculate the actual value for a hospital's costs per case-mix adjusted discharge. Sometimes, hospital MCR records are not comprehensive across all possible data entry fields. Because of this, it is essential to isolate the figures essential to at least derive a CMAD value for a given hospital. Variables meeting this criterion are *Hospital Costs, Hospital Discharges,* and *Hospital Revenue.* A hospital MCR record missing any of these variables was removed from the analysis. The impact of this data scrubbing step (along with all other data scrubbing steps) is provided in

[49] Updated MCR data can be found at Centers for Medicare and Medicaid Services: http://www.cms.hhs.gov/CostReports/CostReportsFY/list.asp#TopOfPage

Appendix F. We did not artificially "fill in" this missing information as this would reduce the variability inherent in the data; moreover, it would have created spurious information. If these data points were not removed, then in the "Final Data Check" described below, they would have been flagged as outliers of calculated CMAD values and removed. Consistent with industry standards for handling missing information, we removed such MCR records.

- **Regression Level Data**

  Regression level data is defined as any additional information known about the hospital which could be used as an independent variable in the regression analysis. These types of variables were put through many tests to ensure that anomalous or outlying data was removed in order to yield an unbiased analysis. Each variable was first arrayed at a total magnitude level to check if any values appeared larger or smaller than the rest of the population. These outlying values were flagged as questionable and the entire record was later removed. The criteria for flagging are described in more detail in Appendix F. Multiple "common-sense" checks were also made to ensure that contradictory information was not reported – e.g. hospitals reporting days without associated costs or discharges, or the number of days or discharges by payor exceeding the known total. Records meeting these criteria were also flagged and later removed. A complete list of these criteria is also included in Appendix F.

- **Sample Audit**

  After compiling all of the hospital records in the MCR dataset, **srHS** ran a random sample audit of the data to determine whether or not the records within the dataset matched, on an individual field level, to a separate source for hospital MCRs. A complete audit over nearly 40,000 records was not feasible given the magnitude of the task and the timeframes available. The website, http://www.costreportdata.com (Cost Report Data), was used for this audit. This website compiles all hospital MCRs using the same source as in our analysis: CMS. Because of the number of fields involved in the MCR dataset, ten records were chosen at random in order to verify that all of the entries for each of the fields matched those online though Cost Report Data. All of the fields were verified, and a summary table for the records checked is located in Appendix C.

  Cost Report Data was also used, when possible, to verify that the records removed during the regression outlier check described in the preceding section were reported the same in the online database as in the analysis database. This ensured that the records were directly compiled as reported on the hospital's cost report to CMS.

Calculations

When performing calculations for CMAD, attention was paid to the statutory guidelines set forth in Public Law 2005 (PL 2005), Chapter 394. This statute lays out the calculation as in Figure 18:

Figure 18: CMAD Formula

$$\frac{\textbf{(A)}\text{ Hospital Only Expenses} - \textbf{(B)}\text{ Bad Debt} - \textbf{(C)}\text{ Hospital Taxes}}{\textbf{(D)}\text{ Inpatient Discharges } \textbf{x} \textbf{ (E)}\text{ All Payor CMI} \quad \text{X} \quad \dfrac{\textbf{(F)}\text{ Total Gross Patient Service Revenue}}{\textbf{(G)}\text{ Gross Inpatient Service Revenue}}}$$

When calculating the value for each hospital's costs per case-mix adjusted discharge, the following steps were undertaken:

A. Hospital's total hospital-only expenses

The total costs incurred were taken from each hospital's MCR. Costs associated with the following non-hospital cost centers were removed:

Skilled Nursing Facilities
Nursing Facilities
Other Long Term Care Facilities
Hospital-owned physician practices
Swing Beds

The net total cost figure represents each hospital's total hospital-only expenses.

B. Hospital's bad debt

The cost figures in worksheet C of each hospital's MCR are already net of all bad debt that is not a Medicare allowable cost. Per the Medicare Cost Report definition, there is a small portion of Medicare allowable bad debt associated with copays and deductibles from Medicare payors. These figures are reported within the MCR after a CMS-required costing adjustment by non-critical access hospitals (CAHs), and were removed accordingly per the formula above. Thus, the final costs used for each hospital are completely net of any bad debt incurred.

C. Hospital taxes paid to the State

The amount of the hospital provider tax levied on each hospital and paid to the State was removed according to figures provided by the Maine Health Data Organization (MHDO).

D. Inpatient Discharges

Inpatient Discharges are pulled directly from the hospital's MCR. These represent the total discharge volume for the hospital at the inpatient level.

E. All Payor CMI

The all payor case-mix index was calculated using multiple data sets as described in ALLPAYOR CONVERSION.xls. This adjustment is made to severity-adjust the experience of each hospital across all payors' discharges.

F & G. Gross Patient Service Revenue (GPSR)

Each hospital's GPSR is reported on the MCR at both the inpatient and total level. This adjustment is used to create a proxy for the total volume passing through each hospital, inclusive of outpatient services.

Final Data Check

After calculating the value for each hospital's costs per case-mix adjusted discharge, the calculated values for each hospital and year were arrayed. It is customary in a study of this size to remove the top- and bottom-most outlying values in order to screen against their undue potential impact on analyses. Accordingly, the top and bottom 1%, a commonly used threshold, of the calculated CMAD values were flagged and later removed.

METHODS

The purpose of this analysis is to estimate the relationship between the Dirigo health reform and the average cost per hospitalization. To do this, it is first necessary to estimate the statistical significance and strength of the relationship between Dirigo and average CMAD values in the State of Maine. The basic task is to estimate the difference between actual observed spending with the Dirigo health reform and projected spending in the absence of Dirigo. As with the Bad debt and charity care (BD/CC) analysis, the key challenge is to identify suitable control groups because in this analysis, we again lack data from randomized trials, the gold standard for program evaluations.

The basic estimation task is to compare the experience of hospitals in the target population (the "treatment group") that were exposed to Dirigo to the experience of hospitals in control group populations that were not exposed to Dirigo. By "treatment group" we mean the group of hospitals who plausibly could be affected by the Dirigo program. All hospitals in Maine are in the Dirigo "treatment group", so clearly hospitals were not assigned randomly to treatment and control groups. In an ideal study, we would be able to randomly assign hospitals to Dirigo and "not Dirigo". In the absence of randomization, we must find suitable control groups.

Any evaluation including a treatment group must answer the question, "Compared to what?" The general answer is, "Compared to the control group". The purpose of the control group is to provide information on the experience of a member of the target population in the absence of the intervention. Control groups often are said to provide information on the "secular trend" in the dependent variable – another way of saying what the experience of the treatment group would have been in the absence of the demonstration. Secular trends are particularly important in this study because nationally hospital's costs were changing during the post Dirigo period. Changes in hospital costs tend to be cyclical, so not controlling for the cyclical trend could lead to false attribution of cost savings to Dirigo. For example, if CMAD was at a "high point" in the cycle, then a slowdown in increases in CMAD could be inappropriately attributed to Dirigo. This phenomenon is sometimes, incorrectly, referred to as "regression to the mean".

Some statistical analysts refer to the information provided by the control group as a "counterfactual". Pure counterfactuals are impossible to establish because it never is possible to observe the same subject experiencing and not experiencing the treatment at exactly the same point in time. The perfect control group is a group that is identical to the treatment group in every respect, except for the fact that the control group was not exposed to the intervention. Thus, all control groups are an approximation to the ideal.

The gold standard for control groups is that found in large randomized trials, and even in randomized trials the validity of the control group can be threatened by selective attrition. In randomized trials, individual hospitals in the target populations are assigned randomly to the treatment and control groups. Because randomization was not possible in this evaluation, our analysis was limited in certain ways. Lack of randomization introduces the possibility of omitted variables bias. The difficulties associated with non-randomization are alleviated to the extent that the control groups provide good estimates of the experience of hospitals like those in the treatment groups in the absence of Dirigo. Addressing the comparability of the treatment and control groups on unobservable variables would require an instrumental variable or selectivity estimation approach, which was not available for this evaluation given the datasets used.

Our key strategy in this analysis was for hospitals to serve as their own controls. For the CMAD analysis we have true panel data, and observe the same exact hospitals both before and after the implementation of Dirigo. This allows the use of more powerful statistical models which are more effective at explaining variation in the data.

To explain our estimation approach, we again begin with a simple linear model. Our basic model is:

$$Y_{ijt} = \beta_0 + X_{ijt}\,\beta + \beta_M M_{ij} + \beta_p P_{jt} + \beta_I\,[M_{ij} \times P_{ijt}] + u_{ijt} \qquad (2)$$

where the subscripts i, j and t stand for the i^{th} hospital in the j^{th} state in the t^{th} time period. Let t indicate the post-Dirigo time period and t-1 indicate the pre-Dirigo time period, and:

Y = CMAD

X = a set of control variables, including an intercept term

M = 1 if the observation is from Maine and 0 otherwise.

P = 1 if the observation is from the post-Dirigo period and 0 if the observation is from the pre-Dirigo period

u = unobserved error.

In this model, the baseline value of CMAD is given by β_0. The difference between Maine hospitals and hospitals in other states is given by β_M. The difference between the pre and post Dirigo time period (in all states) is given by β_p. β_p thus controls for differences in CMAD due to factors common to all states. Finally, β_I is the difference between Maine and other states in the difference in CMAD pre and post Dirigo. Thus, the difference in these two differences, which is the "treatment effect", is β_I. This model is known in the econometrics literature as a standard "difference in differences" model.

Shown differently, we use non-Dirigo states (that is, all states but Maine) as a control group because they did not implement Dirigo and thus would not be expected to have Dirigo effect. Figure 19 below displays the average cost of CMAD for Maine and other states pre and post Dirigo:

Figure 19: Dirigo Effect Overview

	Other States	Maine
Pre Dirigo	a	b
Post Dirigo	c	d

The next chart in Figure 20 explains what each coefficient in the regression represents:

Figure 20: Regression Coefficient Overview

Coefficient	Calculation
β_0	a
β_M	b-a
β_p	c-a
β_I	(d-b)-(c-a)

In this model, β_0 is again the baseline average (a) because both Maine and Dirigo are zeroed out (M=0 and D=0). β_p represents the pre and post Dirigo time trend nationally (M=0 and P=1), β_M represents the differences between Maine (setting M=1 and P=0) and other states pre-Dirigo and β_I represents the difference in the changes over time (M=1 and P=1). This structure controls for the national time trend and identifies the true impact of Dirigo on CMAD in Maine.

Our dataset in this model is true panel data in the sense that we observe the same hospital at multiple points in time. This creates both challenges and opportunities. The challenge is that the error term may be correlated among the observations in our data. Correlations among error terms reduce the amount of statistically *independent* data available to estimate the treatment effect, and thus reduce statistical power. Failure to account for such correlations can lead to erroneous conclusions – suggesting that an estimated treatment effect is statistically significant, when it is not. The hospital specific effects can be modeled with either a fixed or random effect. We included a fixed state effect and included time as a continuous variable to minimize the multicollinearity between the difference and difference estimator and the time effect.

Model Description: Dependent Variable

The dependent variable in this analysis is CMAD which is defined according to the statutory regulations and calculated as described previously.

Model Description: Independent Variables

In our model, we want to control for factors other than the Dirigo initiative that may affect costs in hospitals in Maine. There is a substantial literature that has examined hospital costs. Some of the key factors that have been identified in previous work are size, technological sophistication, teaching status, use of residents, patient characteristics and the severity of conditions treated.

We have a number of different proxies that can be used for size, including number of discharges, number of beds and volume of cases. These different variables are highly correlated with one another, as shown in Figure 21:

Figure 21: Correlation Between Beds, Patient Days, and Patient Discharges

	Beds	Patient Days	Patient Discharges
Beds	1		
Patient Days	0.9647	1	
Patient Discharges	0.9399	0.9655	1

We have selected “beds” as our only measure of hospital size. There are two potential problems with including the other two variables. First, the high degree of collinearity in the model will tend to lead to inflated standard errors. Although we can include all of these variables in the model without introducing bias, the inflated standard errors impede our ability to draw conclusions from the data. Second, patient discharges are used to calculate the dependent variable (CMAD). Including the same variable on both sides of the regression equation both introduces the possibility of severe bias and also makes interpretation of the coefficients challenging. Thus we selected a single measure of “size”, including “beds” in our equation.

Next, we created two variables indicating the proportion of discharges from the hospital that were Medicare and Medicaid. Although the payment source does not directly affect cost within the hospital, it may indicate characteristics of the population that is associated with costs. A higher proportion of Medicare patients, for example, may indicate a hospital has an increasing proportion of older patients who may require longer stays or more intense care.

We also included two measures of critical access hospitals. During the Dirigo timeframe, there were a number of hospitals in Maine which converted, potentially changing their costs in an important way. Thus we created two indicator variables; the first indicates whether the hospital was a critical access hospital (equal to “1” if it is a critical access hospital and “0” otherwise) and a second indicator variable equal to “1” if the hospital transitioned to a critical access hospital that year and “0” otherwise.

For the key analysis variables, we created a indicator variable for “Dirigo” (equal to the variable “P” as described previously) which is equal to “1” for post Dirigo years and “0” for pre Dirigo years. Dirigo is defined as any observation from fiscal year 2004 or later, with fiscal year 2004 spanning the time from July 1, 2003 to June 30, 2004. We also created a “Maine” variable, equal to “1” for hospitals in Maine and “0” otherwise. Finally, we create the “Dirigo Effect” variable, the difference-in-difference variable, as Maine*Dirigo, which will be equal to “1” if the observation is in Maine in the post Dirigo timeframe and zero otherwise.

This does not control for other factors, such as teaching status, tax status and state regulations. To control for these other factors, we employed a fixed effects model. The fixed effects model allows the intercept term to vary across hospitals and is often employed to control for unobserved characteristics that are time invariant. The hospital specific “fixed effect” will control for all hospital specific characteristics that do not vary over time, such as tax status (for profit, not for profit, public), location, physician and staff ability, administrative competence and physical location. To the extent that case mix is constant over the time span, it also will be controlled for in this model. In Appendix G, we present a formal test of the appropriateness of the fixed effects model showing that it is the appropriate specification. We also reviewed how overall trends in the Maine health care market, such as the shift in hospital services from inpatient to outpatient or changes in MaineCare reimbursement may impact the CMAD calculation and found no bias on the CMAD savings calculation[50].

In this analysis, we are using exclusively hospital level data. One other possibility would be to use state averages and to see if average CMAD values in Maine versus other states changed pre and post Dirigo. We did not do this first because the hospital level data allows us to include hospital specific information which allows the estimation of a more precise model. Second, we are concerned that such a state-level analysis would be open to the ecological fallacy (sometimes referred to as "Simpson's paradox") – i.e., that the relationship between Dirigo and CMAD at the state level may not be the same (and could perhaps even be the opposite) of the relationship at the individual hospital level.

Findings

A. Trends in Spending

During the pre Dirigo years (2000-2003), Maine was above the national average in average cost and had greater cost increases to other states. As in Figure 22, in SFY2000, the average cost in Maine was $4,599, while the average in all other states was $4,629, a difference of $30. From 2000-2001, costs in Maine increased faster than in other states, increasing by 9.2% in Maine versus 4.2% in other states. Overall, the average increase in Maine versus other states during the pre-Dirigo years (2000-2003) was 6.8% versus 5.4% in other states over the same time period.

[50] Appendices H and I show how CMAD is affected by a shift of hospital services from inpatient to outpatient and by changes in MaineCare reimbursement levels.

Figure 22: Average Cost per CMAD, Maine and Other States

State Fiscal Year	Maine	Other States	Difference	Percent Change in Maine	Percent Change All other States
2000	$4599	$4629	-$30		
2001	$5022	$4825	$198	9.2%	4.2%
2002	$5481	$5129	$353	9.1%	6.3%
2003	$5608	$5415	$193	2.3%	5.6%
2004	$5770	$5649	$121	2.9%	4.3%
2005	$5993	$5883	$110	3.9%	4.1%
2006	$6030	$6118	-$88	0.6%	4.0%
2007	$6102	$6331	-$229	1.2%	3.5%

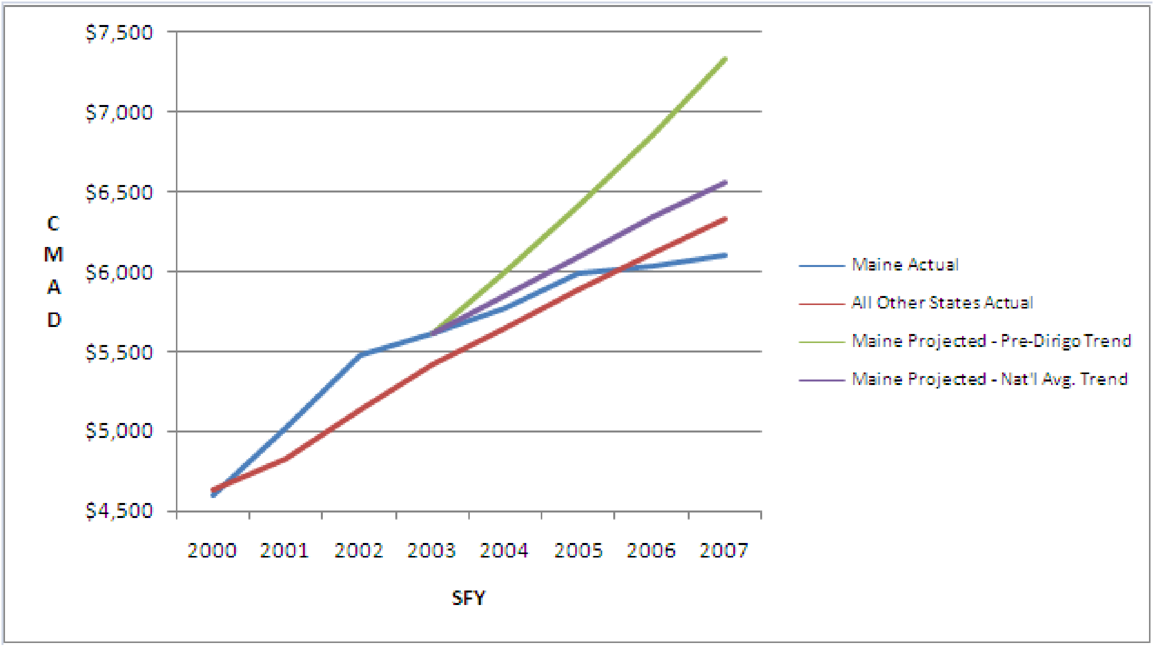
Notes: Excludes Hospitals with Questionable Data and above and below the 1% threshold. Weighted by CMAD Denominator

In the post Dirigo period, the average cost increases in both Maine and other states declined, but the decline was far greater in Maine than in other states. In Maine, the average increase in the 2004-2007 time period was 2.1% versus 4.0% in other states.

This effect can be seen more clearly in Figure 23. Prior to Dirigo (2003), costs in Maine were at or above average costs in other states. After Dirigo, costs in Maine declined relative to other states and has since been consistently below the national average. In Figure 23, we have two simple projections demonstrating the potential effect of Dirigo. First, we projected average costs in Maine if Maine had continued along its pre-Dirigo cost trend, increasing at an average of 6.9% per year. If that had been the case, average costs in SFY2007 would have been approximately $7,324 versus the national average of $6,331 and an actual Maine average of $6,102. This simple analysis suggests that the upper bound of cost savings for Dirigo is approximately $1,222 per event, on average. This is an upper bound because national costs declined somewhat, suggesting that Maine costs were likely to have declined also, even in the absence of Dirigo.

A lower bound can be found by taking the national growth rate and applying it to Maine. If Maine had simply followed the national average, average costs in SFY2007 would have been approximately $6,557, versus the national average of $6,331 and an actual Maine average of $6,102. This suggests that a lower bound estimate of cost savings in Maine is approximately $455 per event, on average. This is a lower bound because, historically, costs in Maine were growing faster than the national average; this estimate thus makes the assumption that costs in Maine would return to the national average in the absence of any policy intervention.

Figure 23: Average Spending in Maine vs. Other States (Non-Regression Trending)



Notes: Excludes Hospitals with Questionable Data and above and below the 1% threshold

B. Regression Analysis

There are several possible ways to specify the dependent variable, CMAD, and also several possible ways to estimate the model. In this analysis (Figure 24), we present results using the natural log of CMAD as the dependent variable and a fixed effects model. This is the preferred model because it is the most appropriate model both theoretically and empirically. In Appendix G, we present results using different model specifications and with CMAD (unlogged) as the dependent variable and relaxing different assumptions made in the estimation. The results are robust to the various specifications.

In this model, there is no "Maine" specific effect. This is because we include fixed effects for hospitals, and "Maine" is implicitly embedded in the Maine hospital fixed effects. Said differently, the Maine hospital fixed effects are perfectly multicollinear with the Maine indicator variable, making it unnecessary (and mathematically impossible) to include it in the model explicitly. We also tested for heteroskedasticity (non-constant error terms). We found evidence that heteroskedasticity was an issue in our analysis and have adjusted for it by using robust standard errors.[51]

Figure 24: The Effect of the Dirigo Health Reform on CMAD

	Coefficient	Robust Standard Error	t statistic	P>|t|[52]	95% Confidence Interval	
Dirigo Year	-0.0011	0.0026	-0.45	0.654	-0.0061	0.0039
Dirigo Effect	-0.0367	0.0184	-2.00	0.046	-0.0727	-0.0007
Percent of Hospital Days Medicaid	-0.0370	0.0303	-1.22	0.222	-0.0964	0.0224
Percent of Hospital Days Medicare	0.3605	0.0266	13.54	0.000	0.3083	0.4127
Number of Residents	-0.0002	0.0001	-2.80	0.005	-0.0004	-0.0001
Number of Beds	0.0001	0.0000	1.66	0.098	0.0000	0.0001
State Fiscal Year	0.0460	0.0006	71.96	0.000	0.0447	0.0472
Transition to Critical Care Hospital	-0.1883	0.0683	-2.76	0.006	-0.3222	-0.0545
Critical Care Hospital	-0.1394	0.0622	-2.24	0.025	-0.2614	-0.0175
Constant	-83.7280	1.2787	-65.48	0.000	-86.2342	-81.2217

Notes: Excludes Hospitals with Questionable Data and above and below the 1% threshold

Linear regression, absorbing indicators

Number of obs = 35383
F(9, 29388) = 1894.78
Prob > F = 0.0000
R-squared = 0.8949
Adj R-squared = 0.8735
Root MSE = .12303

This analysis finds that Dirigo had a statistically significant effect on average CMAD costs. The coefficient (-0.0367) indicates that Dirigo reduced costs and that the results were statistically significant (p=0.046).

[51] We also tried clustered standard errors and the results were consistent.

[52] This p value reflects a "two tailed hypothesis". That is, the null hypothesis tested is that the coefficient is equal to zero, and the alternative is that it is not equal to zero. One may reasonably argue that a positive coefficient is not reasonable in this application; that is, the hypothesis that Dirigo *increased* costs is implausible. This argues that a more reasonable test would be a null hypothesis that the coefficient is equal to zero with an alternative hypothesis that the coefficient is negative. Under that scenario, the null hypothesis would be rejected with a p value of 0.0228.

The model overall performs well. The coefficients all have the expected signs. The overall time trend (β =0.046) is positive, indicating that costs increased over time. The R^2 coefficient (0.8949) is high indicating that the model explained more than 89% of the variance in CMAD (logged). The hospital level fixed effects were also quite significant indicating that the fixed effects model was appropriate.

The dependent variable is the natural log of CMAD so the coefficient as presented in the model relates the impact of Dirigo to the level of logged costs, not costs. However, this coefficient can be interpreted by taking the antilog of the estimated coefficient, subtracting one then multiplying by 100[53,54]. Thus the effect of Dirigo is given by: $(e^{-0.0367}-1)*100$, which equals -3.60. This then suggests that Dirigo reduced CMAD costs by 3.6%, on average across all years of the program.

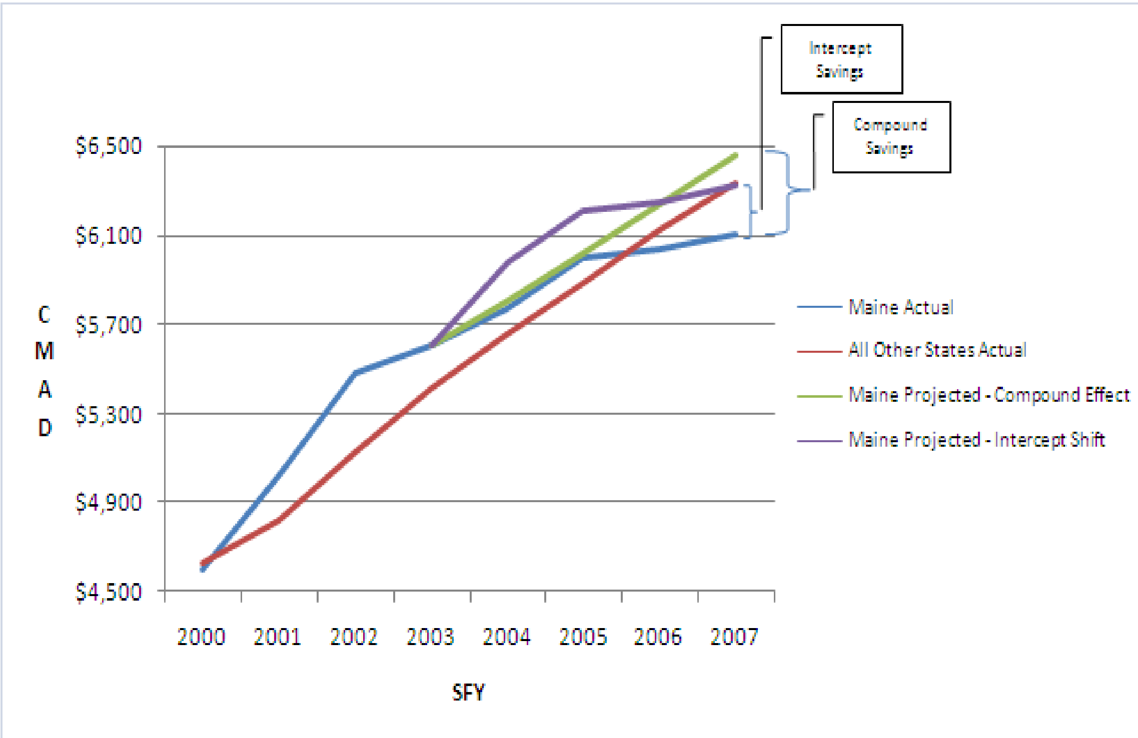
C. Cost Savings Associated with Dirigo

The regression analysis finds that Dirigo reduced average CMAD costs by 3.6% per hospitalization. The analysis essentially finds that without Dirigo, CMAD costs in Maine would be near the average cost for all states, as was the case prior to the implementation of Dirigo.

If we assume that the effect was cumulative (that is, the savings was 3.6% per year compounded over time), then the per hospitalization effect of Dirigo in SFY2007 was a savings of $359. Using a more conservative approach, called an intercept shift, that has the effect of spreading the cost savings equally over the intervention period, the cost savings are $220 per hospitalization. Figure 25 shows average cost with and without Dirigo, illustrating the savings graphically using the compounded approach as well as the savings using the recommended intercept shift approach.

[53] Robert Halvorsen and Raymond Palmquist, “The Interpretation of Dummy Variables in Semilogarithmic Equations,” American Economic Review. 70(3): 474-475.
[54] Damodar Gujarati. Basic Econometrics, 4th Edition.

Figure 25: Effect of Dirigo on Average CMAD Costs, Maine with and without Dirigo vs. Other States (Regression-based Trending)



Cost-Based Reimbursement Adjustment

There were a total of 380,435 case-mix adjusted inpatient and outpatient equivalent discharges in SFY2007. This total volume figure represents experience from the entire Maine "Representative Hospital[55]." A downward adjustment was applied to this volume figure to reflect costs and discharges from a cost-based reimbursement environment, i.e. critical access hospitals and non-critical access Medicaid outpatient experience. The 380,435 figure for total inpatient and outpatient volume was reduced by 74,346 (58,937 discharges and outpatient discharge equivalents from critical access hospitals + 15,409 outpatient discharge equivalents from the non-critical access Medicaid outpatient population), which resulted in an adjusted total volume of 306,089 for SFY2007.

The total CMAD savings associated with Dirigo is equal to 306,089*$220 = $67,339,580.

[55] Representative Hospital calculated as the weighted average of all hospitals in Maine

CONCLUSIONS

The analysis above finds that without Dirigo, CMAD costs in Maine would be higher than it is with Dirigo. To determine overall savings to the Maine health care system, the reduction in CMAD costs must be applied to the appropriate discharge figure for 2007. The total CMAD savings associated with Dirigo is equal to 306,089*$220 = $ 67,339,580.

Note that the estimated savings are below what we had earlier termed a lower bound of estimated costs savings. Using trend data, we found that if we simply assumed that Maine had continued along its pre-Dirigo cost trend, increasing at an average of 6.9% per year, cost savings would have been $1,222 per event, on average. If we assumed that after Dirigo, Maine followed the national average, cost savings would have been $455 per event, on average. We find that cost savings are only $220 per event, on average. This result is largely due to conversions of Maine hospitals to critical access. If we take out the conversion and critical access coefficients (as shown in appendix G), the estimated cost savings per event is 6.01%, or $367 per event, in line with the lower bound estimates.[56]

[56] Calculated as (6,102*1.0601) - $6,102.

4. YEAR 4 AMCS CALCULATIONS – OVERLAP

OBJECTIVE

As discussed previously, savings are realized under each of the Dirigo initiatives; BD/CC and CMAD. The natural question to ask is whether there might be any overlap in the AMCS Year 4 savings calculations used for each of the initiatives. We examined the methodologies used to estimate savings in Year 4 and identified potential areas of overstated savings (in past years referred to as double counting) as well as understated savings (in past years referred to as under counting). In this section, the areas of overlap are presented with detailed descriptions of the drivers, illustrations where appropriate, and quantifications where the direction of overlap can be determined.

We have organized this section into the following:

- Areas of Overlap
- Conclusions

AREAS OF OVERLAP

Before discussing the potential areas of overlap between BD/CC and CMAD savings calculations, we need to review the concepts underlying each calculation. For BD/CC, savings to paying customers are generated by reduced cost-shifting, thus reducing claims costs, as a result of previously unreimbursed services now being reimbursed due to a reduction in the uninsurance rate as a result of Dirigo. For CMAD, savings to paying customers are generated due to a reduction in intrinsic hospital costs, thus reducing claims costs; it is most informative to examine the CMAD formula (Figure 26) to determine how savings are calculated. As shown in the statutory formula and discussed below in more detail, reductions in BD/CC are not reflected 1:1 in the CMAD calculation.

- Bad debt is not included as a net hospital expense. The formula below illustrates the reduction of gross hospital expense for appropriate bad debt. (A) Hospital-only expenses as reported on the MCR are net of non-Medicare allowable bad debt. (B) Medicare allowable bad debt is subtracted, as noted in steps 168-175 of Appendix C, from (A).
- As a result, there is no bad debt in the numerator of the statutory CMAD formula and therefore there can be no 1:1 reduction in CMAD savings due to BD/CC savings.

Figure 26: CMAD Formula with Potential Overlap Components

CMAD Formula

$$\frac{\textbf{(A)}\text{ Hospital Only Expenses} - \textbf{(B)}\text{ Bad Debt} - \textbf{(C)}\text{ Hospital Taxes}}{\textbf{(D)}\text{ Inpatient Discharges } \mathbf{x}\ \textbf{(E)}\text{ All Payor CMI} \times \dfrac{\textbf{(F)}\text{ Total Gross Patient Service Revenue}}{\textbf{(G)}\text{ Gross Inpatient Service Revenue}}}$$

The formula laid out in Figure 26 is the same as the statutory formula set forth in Figure 18 per PL 2005, Chapter 394. The first component of the numerator, (A), corresponds to hospital only expenses contained in the MCRs, already net of non-Medicare-allowable bad debt (worksheet C is already net of this component of uncompensated care), and reduced for non-hospital cost center expenses. The second component of the numerator, (B), is the Medicare-allowable bad debt, which when subtracted from (A) leaves no bad debt in the numerator. The cost of charity care is contained in (A) as it is part of the expenses incurred by the hospital and reported on the MCRs. Note however that a reduction in charity care does not result in a reduction to (A); it simply results in the expense being reclassified from charity care expense to normal hospital operating expense and the total value of (A) remains unchanged.

BD/CC and CMAD Overlap – Pre-Existing Service Utilization of Previously Uninsured

Consider the scenario where the only savings initiative under Dirigo is to reduce the uninsurance rate. Prior to Dirigo, there are pre-existing hospital services for which there is no reimbursement and are provided as charity care or are written off as bad debt. The hospital recovers some of these costs via cost-shifting to paying individuals and insurance carriers. After Dirigo, with a reduction in the uninsurance rate, a portion of the above pre-existing services are reimbursed via the new insurance coverage and paid for through new premium payments, resulting in savings to the hospital that can be transferred to insurance carriers via a reduction in the cost-shifting. Note that regardless of insurance status, the total pre-tax hospital cost remains the same in the system pre and post Dirigo. There has been no change in the amount of those previously unreimbursed hospital costs, just in the addition of new revenue sources for those previously unreimbursed costs and therefore insurance carrier savings associated with a reduction in cost-shifting. This latter savings is captured within the BD/CC savings calculation.

In previous proceedings, it was argued that the CMAD calculation overlapped with BD/CC savings based on the assumption that the numerator of the CMAD calculation has decreased as a result of the Uninsured/Underinsured initiatives. In fact, that is not the case. Figure 27 below shows that post-Dirigo BD/CC initiative, the CMAD numerator based on the MCR-reported costs would be higher since non-Medicare-allowable bad debt (BD), which is already removed from the MCRs, would go down and thus cause the CMAD numerator to rise. Charity care (CC) costs would simply convert from charity care costs to insured costs and so would not impact the CMAD numerator. Taxes would increase slightly since revenue rises, but since the costs on the Maine MCRs are gross of taxes, there is no net effect on the CMAD numerator. As a result, the impact of the BD/CC overlap is to understate savings attributable to CMAD.

Figure 27: Effect of Providing Coverage on Total Hospital Costs

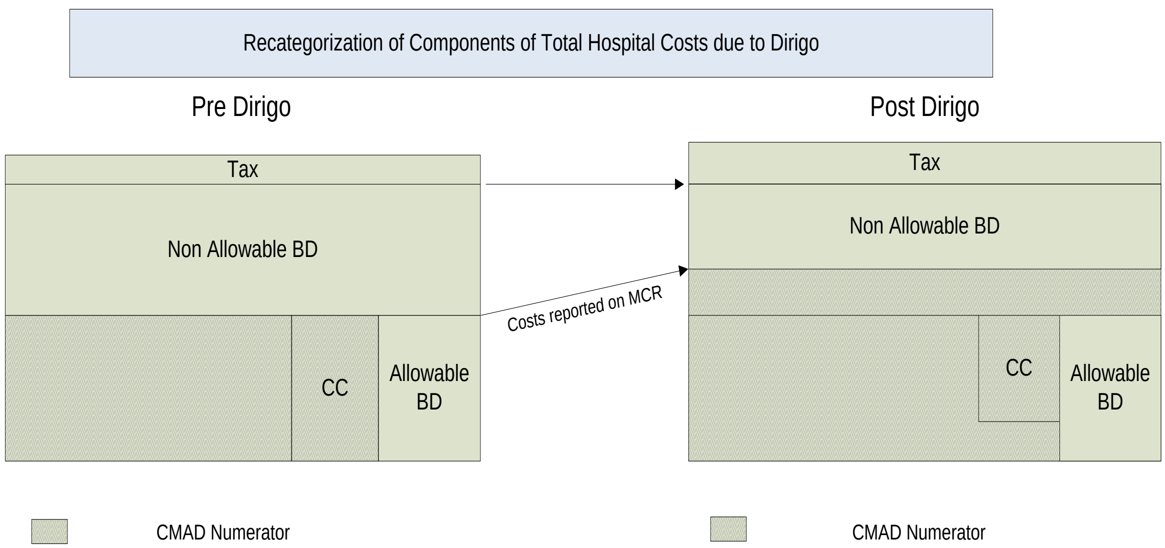


Figure 27 looks only at the numerator. If one looks at the complete CMAD formula and how it might be impacted by an increase in BD/CC revenue, it is indeterminate how an increase in BD/CC revenue might exactly impact the CMAD calculation. For the denominator of CMAD, the discharges and CMI do not change from pre-Dirigo to post-Dirigo by using the MCRs and the statutory formula. It is not possible to anticipate how the outpatient volume adjustor (revenue ratio) might change in light of increased revenue sources to cover previously unreimbursed services.

Figure 28 below illustrates the potential impact of BD/CC on the CMAD savings calculation. It shows how certain elements of the CMAD calculation are affected by the previously uninsured now having insurance coverage – some elements increase, some decrease, while others are indeterminate. Correspondingly, their impact on CMAD and (converse) impact on CMAD savings could be an increase, decrease or indeterminate impact on savings. To visualize the impact of the BD/CC initiative on CMAD savings, or, the impact of the movement of uncompensated care to compensated care on the statutory CMAD formula as calculated from the MCRs, the graphic below can be helpful to understand the CMAD numerator:

Figure 28: Impact of BD/CC on CMAD Formula Components (Pre-Existing Utilization)

Effect of BD/CC Reduction on CMAD Formula Components

Pre-Existing Service Utilization*
by Previously Uninsured

CMAD Formula Component	Impact	Rationale	Effect on Calculated CMAD	Effect on Savings
Hospital Only Expenses	↑	Hospital only expenses will increase as reported on the MCR because non-allowable Medicare bad debt, which was previously not reported, will now appear as costs. The increased provider tax due to increased revenue will also drive this figure slightly upward.	↑	↓
Bad Debt	Allowable ↔ Non-Allowable ↓	There should be negligible effects on the Medicare-allowable bad debt because the Dirigo initiative should not affect the Medicare population much. Non-allowable bad debt will decrease due to the uninsured gaining coverage. Because the non-allowable bad debts are not included in the cost report, receiving compensation for these will result in a higher reported cost figure than had the bad debts remained non-allowable.	↑	↓
Hospital Tax	↔	Tax increases because it is based off of revenue, which increases. Costs on the cost report are gross of this tax, though, so any increase will also be reflected in the total costs and netted out in the end.	↔	↔
Inpatient Discharges	↔	Inpatient Discharges do not change under pre-existing utilization because the discharges used are independent of payment status – ie. discharges include all hospital experience in both settings.	↔	↔
Case-Mix Index	↔	Case-Mix Index will not change under old utilization because the same mix of services will be used to calculate the index.	↔	↔
Outpatient Volume Adjustor	?	The revenue received by the hospital will increase as more individuals become insured and uncompensated care lessens. The degree to which this will happen quicker at the inpatient or outpatient level is indeterminate. The effect on the ratio is unknown.	?	?

* Service utilization level that existed in the absence of Dirigo

BD/CC and CMAD Overlap – New Utilization of Previously Uninsured

Similar to Figure 28, the table in Figure 29 outlines the impact of new utilization by the previously uninsured on CMAD and CMAD savings calculations. As in the discussion of pre-existing utilization, here too the impact on CMAD savings when examining individual variables is indeterminate and cannot be calculated.

Figure 29: Impact of BD/CC on CMAD Formula Components (New Utilization)

Effect of BD/CC Reduction on CMAD Formula Components

New Service Utilization*
by Previously Uninsured

CMAD Formula Component	Impact	Rationale	Effect on Calculated CMAD	Effect on Savings
Hospital Only Expenses	↑	Hospital only expenses will increase as reported on the MCR because non-allowable Medicare bad debt, which was previously not reported, will now appear as costs. Also new service utilization will increase costs by definition. The increased provider tax due to increased revenue will also drive this figure slightly upward.	↑	↓
Bad Debt	Allowable ↔ Non-Allowable ↔	The new service utilization will be from those individuals newly insured. Only a very small number of these individuals should create Medicare-allowable bad debt. There should be a very small increase to non-allowable bad debt for those insured individuals who cannot pay their member cost share.	↔	↔
Hospital Tax	↔	Tax increases because it is based off of revenue, which increases. Costs on the cost report are gross of this tax, though, so any increase will also be reflected in the total costs and netted out in the end.	↔	↔
Inpatient Discharges	↑	Discharges will increase under new service utilization because an individual who has just received insurance will use more services.	↓	↑
Case-Mix Index	?	This effect cannot be determined because one cannot tell the mix of new services that will be used by this newly insured population.	?	?
Outpatient Volume Adjustor	?	Under new utilization each component of the ratio will increase because Net Total Costs increase, but it is impossible to tell which component will increase more.	?	?

* New level of service utilization by the previously uninsured that is created by the presence of Dirigo

BD/CC and CMAD Overlap – Reduced Downward Pressure on Costs due to Insurance Reimbursement for Previously Uncompensated Care

In light of additional revenue for previously unreimbursed hospital costs, hospitals could choose to reduce the downward pressure on costs caused by the voluntary target. In other words, the hospitals may not lower their costs to the fullest extent possible. The net result of this action however, would be to raise the actual observed CMAD in the presence of Dirigo, thus causing the amount of savings to be under-counted due to the interaction of BD/CC and CMAD, not double-counted.

Since it is not possible to measure how hospitals react to additional revenue in terms of managing costs, the potential underestimation of CMAD savings is indeterminate and has not been quantified. Moreover, it seems unlikely that, given the arguments the MHA has made in the past that Maine hospitals are in poor financial condition, they would choose to reduce their downward pressure on costs as the net effect of reducing that downward pressure would be a reduction in operating margin.

CONCLUSIONS

The AMCS Year 4 methodology for BD/CC and CMAD savings calculations has potential areas of overlap. Overlap can cause understated savings figures as well as overstated savings figures.

As illustrated above, the reduction in uncompensated care due to Dirigo actually increases the calculation of CMAD in the post-Dirigo time period, so that the CMAD savings calculated is understated (lower than what it would have been had there been no BD/CC initiative). Additionally, the reduction in uncompensated care costs could also hypothetically result in understated savings due to reduced pressure to control costs, but since the quantification was indeterminate, corresponding savings increases were not calculated. Figures 30 and 31 below summarize our overlap analysis:

Figure 30: Summary of Overlap between BD/CC and CMAD – Savings Understatement

Area of Overlap	Initiatives	Description	Direction	Savings Overlap
1	BD/CC:CMAD	CMAD savings understatement resulting from Dirigo reducing the uninsured rate and increasing allowable costs on MCRs	Savings understatement	Indeterminate
2	BD/CC:CMAD	Lowered pressure on cost reductions due to additional insurance reimbursement for pre-existing utilization in uncompensated care	Savings understatement	Indeterminate

Figure 31: Summary of Overlap between BD/CC and CMAD – Savings Under-or-Overstatement

Area of Overlap	Initiatives	Description	Direction	Savings Overlap
3	BD/CC:CMAD	CMAD volume increase due to new utilization of services by the previously uninsured	Savings under-or-overstatement	Indeterminate

APPENDIX A: ABBREVIATION LIST

Abbreviation/Acronym	Definition of Abbreviation/Acronym
Agency	Dirigo Health Agency (DHA)
AHD	American Hospital Directory
AHRQ	Agency for Health Care Research & Quality
AMCS	Aggregate Measurable Cost Savings
ARF	Area Resource File
ASCII	American Standard Code for Information Interchange
ASEC	Annual Social and Economic Supplement
Board	Board of Trustees
BD	Bad Debt
BD/CC	Bad Debt and Charity Care
CAH	Critical Access Hospital
CC	Charity Care
CMAD	Cost per Case-Mix Adjusted Discharges
CMI	Case-Mix Index
CMS	The Centers for Medicare & Medicaid Services
COM	Consolidated Operating Margin
CPS	Current Population Survey
CY	Calendar Year
DHA	Dirigo Health Agency
DHHS	US Department of Health and Human Services
Dirigo	State of Maine's Dirigo Health Reform Act
DRG	Diagnosis-Related Group
ESI	Employer Sponsored Insurance
FIPS	Federal Information Processing Standard
FPG	Federal Poverty Guideline
FPL	Federal Poverty Limit
GPSR	Gross Patient Service Revenue
HCUP	Healthcare Cost & Utilization Project
HFY	Hospital Fiscal Year
HHS	Health and Human Services
HIFA	Health Insurance Flexibility and Accountability
HIU	Health Insurance Unit
HRSA	Health Resources and Services Administration
ID	Identifier
I/P	Inpatient
IPPS	Medicare Inpatient Prospective Payment System
Maine or State	State of Maine
MCR	Medicare Cost Reports
MedPar	Medicare Provider Analysis and Review
MEPS	Medical Expenditure Panel Survey
MHA	Maine Hospital Association
MHDO	Maine Health Data Organization

Abbreviation/Acronym	**Definition of Abbreviation/Acronym**
MSA	Metropolitan Statistical Area
NF	Nursing Facility
NIU	Not In Universe / Labor Force
OLS	Ordinary Least Squares
O/P	Outpatient
OTC	Other Long Term Care
PL	Public Law
RHC	Rural Health Center
SAS	Statistical Analysis System
SCHIP	State Children’s Health Insurance Program (now CHIP)
SID	State Inpatient Dataset
SFY	State Fiscal Year
SNF	Skilled Nursing Facility
srHS	**s**chramm▫**r**aleigh **H**EALTH **S**TRATEGY
US	United States

APPENDIX B: SUMMARY OF BD/CC DATA MANIPULATIONS

Overview	**Description**	**Reference***
ASEC Data: • Import March CPS and supplementary data components: revised insurance extract and FIPS codes files.	ASEC data is uploaded from the National Bureau of Economic Research website, following instructions outlined in the log;	Line:14-82
	Health insurance supplement files are obtained from the Census Bureau;	Line:84-122
	FIPS codes data come from Bureau of Labor Statistics website;	Line:200-202
• Combine supplementary datasets with core CPS and merge consistently defined annual extracts to form the analytical dataset	Re-code and re-name analytical variables to adjust for changes in survey instrument over the study period: • Race collapsed from 5 categories prior to 2003 and 21 categories starting with 2003 data to a consistent 4 category grouping; • Health insurance supplement files are merged by unique household sequence number with annual CPS data prior to 2005 to obtain flags for employer-provided and private-direct purchase health insurance coverage; • Data from 2000 CPS is merged with FIPS codes supplementary file by state variable defined in terms of Census definitions to include FIPS state definition to 2000 subset; • Identifiers for region, county, and metropolitan area are renamed in surveys prior to 2005 to conventions adopted in more recent surveys;	Line: 220-326 229-246 252-261 280-297 300-315
	Subset annual files to a include only variables needed to create the analytical file and save these extracts;	Line:318-325
	Append annual files to form the analytical dataset;	Line:335-345
Data Recode: • Create HIU	Health Insurance Units(HIU) are constructed using household, family and individual identifiers to group into one unit persons ordinarily eligible for coverage through a family plan;	Line:353-444

Overview	**Description**	**Reference***
• Recode key demographic and socioeconomic data for parents and children	Individual level variables (i.e. age, gender, race, insurance status, disability, and geographic identifiers) are defined for each respondent;	Line:449, 458, 470, 481, 487-513, 606-618, 622-650, 665
	Variables relating to labor force participation, education, and marital status are defined for adults only; Parent values are then imputed for child records;	Line:518-603
	Family variables are evaluated on HIU level and distributed across all members of HIU (i.e. family income, poverty status, etc.).	Line:454,464,475,653
• Express income in terms of Federal Poverty Line	HIU income is contrasted against the corresponding Federal Poverty Guideline (FPG) - by year, state, and HIU size. FPG data are obtained from the Department of Health and Human Services;	Line:622-666
• Add Medicaid and SCHIP Eligibility data	Medicaid and SCHIP income eligibility data acquired from the Kaiser Foundation reports is merged with the core data by year state eligibility group (varying age thresholds were used to assign eligibility for children; eligibility for parents varied according to work status);	Line:677-707
	Create Medicaid/SCHIP identifiers using merged income thresholds, relative HIU income, age group or work status;	Line:710-734
• Recode geographic variables;	Geographic identifiers for state, region, and Census division are created;	Line:739-755
• Add county level data	Employment, firm size, and poverty status variables are summarized at county level for each of the study years; Counties not identified in the survey are grouped into a separate category;	Line:759-793
	Weighted county statistics is merged back with the core data via year and FIPS county identifier;	Line:800-803
• Create a subset of variables required for the analysis and restrict the sample to persons under the age of 65;	Subsets the data to persons under 65;	Line:814
	Restricts the data only to variables required for the analysis;	Line:818-827
	Data are evaluated for consistency;	Line:831-832
	Analytical dataset is saved;	Line:835

Overview	**Description**	**Reference***
MEPS Data: • Data is imported into and subset variables needed to update bad debt charity care estimates;	2002 MEPS data are obtained from the Agency for Health Care Research and Quality (AHRQ) as described in the log;	Line:186-198
	Core data is subset variables needed to update bad debt charity care estimates;	Line:843-848
	MEPS subset is saved;	Line:850
Analysis: • Using program analysis_dirigo_050809	Create a macro containing key control variables for the analysis	Line: 52-60
	Defined sample as adults aged 19-65 not eligible for Medicaid or SCHIP	Line: 66
• Estimation	Probit estimating difference between Maine and other states in uninsurance rate	Line: 70
	Probit estimating difference between Dirigo years and non-Dirigo years in all states in uninsurance rate	Line: 73
	Probit estimating Dirigo effect using difference-in-differences model in all states in uninsurance rate	Line: 77
	Logit estimating Dirigo effect using difference-in-differences model in all states in uninsurance rate	Line: 78
	Calculation of marginal effects from logit	Line: 79
	Probit estimating Dirigo effect using difference-in-differences model in all states in uninsurance rate including state fixed effects	Line: 83
	Logit estimating Dirigo effect using difference-in-differences model in all states in uninsurance rate including state fixed effects	Line: 84
	Calculation of marginal effects from logit including state fixed effects	Line: 85
	Probit estimating Dirigo effect using difference-in-differences model in Northeast only in uninsurance rate including state fixed effects	Line: 88
	Logit estimating Dirigo effect using difference-in-differences model in Northeast in uninsurance rate including state fixed effects	Line: 89
	Calculation of marginal effects from logit in Northeast including state fixed effects	Line: 90

Overview	**Description**	**Reference***
	Probit estimating Dirigo effect using difference-in-differences model in all states in uninsurance rate including state random effects	Line: 94
	Logit estimating Dirigo effect using difference-in-differences model in all states in uninsurance rate including state random effects	Line: 95
	Calculation of marginal effects from logit including state random effects	Line: 96
	Probit estimating Dirigo effect using difference-in-differences model in Northeast only in uninsurance rate including state random effects	Line: 99
	Logit estimating Dirigo effect using difference-in-differences model in Northeast in uninsurance rate including state random effects	Line: 100
	Calculation of marginal effects from logit in Northeast including state random effects	Line: 101

*The Reference file refers to crdata_dirigo_052009_documentation.xls, tab name “Log”, and crdata_dirigo_052009_ProgramMS.doc

APPENDIX C: SUMMARY OF CMAD DATA MANIPULATIONS

Overview	Description	Reference*
MCR Data: • Bring in raw MCR data components and a provider lookup table	Download Medicare Cost Report (MCR) data and related files from the Centers for Medicare and Medicaid Services website.	Step 1
	Imports Numeric, Report, and Alpha data sets for each year from 1998-2008, and imports a provider lookup table.	Steps 2-23, 25-46, 51, 69-90
• Combine the MCR components with each other and the provider lookup table	Merges each year of the Numeric, Report, and Alpha data sets with the other years of the same data set type.	Steps 24, 47-48, 91
	Pulls specific data relevant to the cost per case mix adjusted discharge calculation and the regression analysis off of the Numeric and Alpha data sets, then merges these condensed tables with the Report data set.	Steps 49-50, 59-60, 92-93
	Sums up the Numeric data for values with matching identifying fields, and then merges the numeric data sets and the Alpha data set with the provider lookup table.	Steps 52-56, 61-64, 94-95
	Transposes the resulting data sets by the description of the data. These tables contain relevant cost components and regression data as variables.	Steps 57-59, 65-66, 96-98
	Merges the transposed Numeric data sets together, and then merges the resulting data set with the transposed Alpha data set.	Steps 67-68, 99-101
• Add County and State FIPS codes	Imports, and formats a 5 digit zip code database then merges it with the data set containing all of the Numeric and Alpha data.	Steps 102-106
	Assigns a state Federal Information Processing Standard (FIPS) code based on a record's provider number.	Steps 107-108
Data Adjustments: • State Fiscal Year adjustment	Determines how a record fits within the Maine State Fiscal Year (SFY) and calculates the number of days in the record that fit within the SFY.	Steps 109-116
	Scales data so it reflects the portion of the record that belongs to the SFY.	Steps 117-123
• Add CAH indicator and an All-Payor CMI value	Imports and adds a Critical Access Hospital (CAH) indicator.	Steps 124-129
	Imports and adds Case-Mix Index (CMI) values for each hospital.	Steps 130-156
	Adds the variables County FIPS and State FIPS to the data set. They had been dropped previously to ease calculations.	Steps 157-168
• Data Scrubbing and Final Compilation	Runs a series of reasonableness checks on the data prior to compiling final values.	Steps 169-175
	Flags top and bottom percentile of cost per case mix adjusted discharge values.	Step 176

Overview	Description	Reference*
Analysis:	Read in data and create log files	Line 3-4
• Data preparation	Drop extreme values	Lines 6-7
	Create variables measuring percent of days Medicare, Medicaid, year indicator variables, critical care and transition variables	Lines 9-28
• Analysis	Calculate mean CMAD in Maine and other states by year	Lines 30-32
• Baseline Regression	Baseline CMAD regression using logged dependent variable and robust standard errors	Lines 38
• Tests of Model	Distributional tests, including histograms	Lines 44-48
	Unlogged regression	Lines 52
	Re-read in data to run with all data	Lines 56
	Create variables measuring percent of days Medicare, Medicaid, year indicator variables, critical care and transition variables	Lines 58-76
	Regression with all observations and logged dependent variable	Line 80
	Data sorted by year	Line 84
	Mean CMAD in Maine with all observations, by year	Line 87
	Mean CMAD in Maine excluding hospitals with questionable values, by year	Line 91
	Questionable observations dropped for all states except Maine	Lines 92-93
	Regression with Maine questionable observations included and logged dependent variable	Line 97
	Questionable observations in Maine dropped	Lines 101-102
	Non-fixed effects regression estimated to capture variance inflation factor	Lines 105-106
	CMAD regression using logged dependent variable and robust standard errors with year fixed effects	Line 110
	CMAD regression using logged dependent variable and robust standard errors with random effects estimator	Lines 114-115
	Hausman test for appropriateness of Random Effects Model	Lines 119-123
	CMAD regression using logged dependent variable and robust standard errors excluding measures of critical care and transition	Line 127
	CMAD regression using logged dependent variable and robust standard errors including county measures	Line 131

*Steps referred to are contained within SAS Code.sas and SAS Code Descriptions.xls. Lines referred to are within cmad analysis1.do.

APPENDIX D: MCR DATA SAMPLE AUDIT

Random Spot-Check to Verify SAS Code Correcty Retrieves MCR Data (Data checked against database at http://costreportdata.com)

See file Data Check.zip for in-depth details

Hospital Name	MILLINOCKET REGIONAL HOSPITAL	UVA HEALTHSOUTH REHAB HOSPITAL	RIDEOUT MEMORIAL HOSPITAL	GRITMAN MEDICAL CENTER	BRYN MAWR REHAB HOSPITAL	CLEVELAND REGIONAL MEDICAL CENTER	ST. JOSEPH'S HOSPITAL INC	AURORA LAKELAND MEDICAL CENTER	HILLCREST HOSPITAL	METROPOLITAN STATE HOSPITAL
Provider Number	200003	493029	50133	130011	393025	340021	110043	520102	360230	54133
FY Begin Date	7/1/2002	1/1/2007	7/1/2004	1/1/2002	7/1/2000	1/1/2006	7/1/2002	1/1/2004	1/1/2004	7/1/2004
FY End Date	10/31/2002	12/31/2007	6/30/2005	12/31/2002	6/30/2001	12/30/2006	6/30/2003	12/31/2004	12/31/2004	6/30/2005
Teaching_Status	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Crit_Access_Ind	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
NTC	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Beds	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Days_Medicaid	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Days_Medicare	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Inpatient_Rev	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Medicaid_Disch	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Medicare_Disch	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Tot_IP_Ch	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Tot_OP_Ch	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Tot_Patient_Rev	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Total_Disch	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Type_of_Control	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
days_total	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Uncomp_Cost	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Urban_1_Rural_2	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
SNF_Cost	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
SNF_IP_Ch	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Clinic	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Clinic_IPCH	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Clinic_OPCH	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Swing_Beds	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Interns_and_Res	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
NF_Cost	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
NF_IP_Ch	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
OTC_Cost	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
OTC_IP_Ch	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
Bad_Debt	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
All Fields Correct?	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑

APPENDIX E: CMAD DATA DIFFERENCES ACROSS AMCS YEARS

The refinements made to the AMCS calculations across the years are reflective of feedback from the Maine Superintendent of Insurance and **srHS**' continuous efforts on how to best collect the information in the most comprehensive and efficient manner possible. For example, the Years 1 – 3 CMAD calculations looked only at hospitals within the State of Maine. This enabled **srHS** to gather the MCR information directly from the State. This manual process was no longer feasible when the Superintendent recommended that the methodology evolve into a multi-state, multi-variable regression analysis. Thus, in Year 4, a national dataset was necessary. In response, we have compiled the Year 4 data directly from the CMS website.

The following figures will not only show how the data has changed, at an aggregate level, from AMCS year to year, but they will also explain why these changes occur.

Figure 32. Maine Representative Hospital Cost per CMAD

SFY	Year 1	Year 2	Year 3	Year 4[1]
2000	Representative	$ 4,868	$ 4,882	$ 4,578
2001	Hospital	$ 5,097	$ 5,109	$ 5,029
2002	Not	$ 5,613	$ 5,571	$ 5,481
2003	Created	$ 5,800	$ 5,739	$ 5,608
2004		$ 5,912	$ 5,922	$ 5,770
2005		$ 6,316[2]	$ 6,160	$ 5,892
2006		N/A	$ 6,407[2]	$ 6,030
2007		N/A	N/A	$ 6,102

[1] Includes records with fields flagged as questionable so the same hospitals are compared across AMCS years. These figures will not match those used in the analysis.
[2] MCR Data was incomplete and the figures expressed are partially based off of completion trends

Figure 33: Potential Changes in AMCS Year 4 Data

Data Discrepancy	Material Changes from Years 1 - 3	Example	Rationale
Calculated CMAD values differ between AMCS years	**Data Sources** Sources changed for some data fields	See Figure 34 See Figure 34 for some impacts quantified	When compiling data on a national basis, it is not possible to use Maine-specific data sources such as MHDO for items like discharges and the case-mix index. **srHS** used publically available data sets on a national-level for these values which can cause fluctuations.
	Revenue Figures Revenue is used instead of charges	See Figure 35 for impact on outpatient volume	Per statutory guidelines, revenue figures were used to create the proxy for outpatient volume in the CMAD formula.
	Swing Beds Remove costs associated with swing beds	See Figure 36	Per statutory guidelines, swing beds were removed because they are considered a non-hospital cost center. Reductions are systematic and unbiased.
	Bad Debt Remove Medicare-allowable bad debt	See Figure 36	Per statutory guidelines, bad debt is to be removed from the total costs reported by the hospital. In previous years' calculations, a small amount of bad debt for Medicare members was not removed. The Year 4 calculation makes this adjustment. Reductions are systematic and unbiased.

Data Discrepancy	Material Changes from Years 1 - 3	Example	Rationale
Cost per CMAD growth from SFY 2000 to 2001 increased above previously expressed figure.	**Discharge Source** Inpatient discharges taken directly off of MCR	See Figure 35 - Evidence of discrepancy between Year 3 and Year 4 data See Figure 37 - Evidence that this discrepancy is not due to one anomalous or misreported hospital record, but rather due to the change in data sources seen above.	Discharges were previously received from MHDO. This was not possible at the national level so the MCRs were used to provide this information nationally. The source for Maine's discharges was changed to maintain consistency with the control group states. MHDO source data did not reflect the drop in inpatient discharges seen in the MCR data from years 2000 - 2001, which is the primary driver in the CMAD growth differential.
	SFY 2000 Data SFY 2000 time period expanded from 01/01/2000 - 06/30/2000 to include time from 07/01/1999 - 12/31/1999	See Figure 35	With more available data, it was appropriate to reflect the entire time period of the State Fiscal Year as opposed to the previously used 6 month snapshot. The six months of experience from 07/01/99 - 12/31/99 had a lower value for the cost per CMAD which, when included, caused the SFY 2000 calculated number to decrease and increase the growth percentage between SFYs 2000 and 2001.

Figure 34: Data Sources by AMCS Year

Data Element	Years 1-3	Year 4
Total Costs	Manually pulled from MCR Worksheet C, Line 103, Column 1	Sum of CMS MCR entries: Worksheet B, Lines 20.4-20.99, 21.2-21.59, 21.8-21.99, 25-68, Column 27 and Worksheet C part 1, Lines 62-62.1, Column 5
RHC Costs	Manually pulled from MCR Worksheet C, Line 60.1, Column 1	Sum of CMS MCR entries: Worksheet B part 1, Lines 60-61, Column 27.
SNF Costs	Manually pulled from MCR Worksheet C, Line 34, Column 1	Pulled from CMS MCR Worksheet B part 1, Line 34, Column 27
NF Costs	Manually pulled from MCR Worksheet C, Line 35, Column 1	Sum of CMS MCR entries: Worksheet B part 1, Lines 35 and 35.1, Column 27
OTC Costs	Manually pulled from MCR Worksheet C, Line 36, Column 1	Pulled from CMS MCR Worksheet B part 1, Line 36, Column 27
Medicare I/P Bad Debt	NA	Pulled from CMS MCR Worksheet E part A, Line 21.01, Column 1
Medicare O/P Bad Debt	NA	Pulled from CMS MCR Worksheet E part B, Line 27.01, Column 1
CAH Medicare Bad Debt	NA	Pulled from CMS MCR Worksheet E-3 part 2, Line 25.01, Column 1
Swing Beds	NA	Pulled from CMS MCR Worksheet D-1 part 1, Line 26, Column 1
Tax Allocation	Received from MHDO	Received from MHDO
Total O/P Charges	Manually pulled from MCR Worksheet C, Line 103, Column 7	NA
RHC O/P Charges	Manually pulled from MCR Worksheet C, Line 60.1, Column 7	NA

Data Element	Years 1-3	Year 4
Total I/P Charges	Manually pulled from MCR Worksheet C, Line 103, Column 6	NA
SNF I/P Charges	Manually pulled from MCR Worksheet C, Line 34, Column 6	NA
NF I/P Charges	Manually pulled from MCR Worksheet C, Line 35, Column 6	NA
OTC I/P Charges	Manually pulled from MCR Worksheet C, Line 36, Column 6	NA
Total GPSR	NA	Pulled from CMS MCR Worksheet G2 line 25 column 3
I/P GPSR	NA	Pulled from CMS MCR Worksheet G2 line 25 column 1
Total Discharges	As reported by MHDO	Sum of CMS MCR entries: Worksheet S-3 part 1, Lines 1, 2, 6, 7, 8, 9, 10, 11, 13, and 14-15, Column 15
CMI	All-Payor CMI received from MHDO	Medicare CMI calculated by AHD All-Payor proxy calculated using HCUP data

Figure 35: Calculation Comparison* -- AMCS Year 3 v AMCS Year 4

	AMCS Year 3 Cost per CMAD Growth	AMCS Year 4 Cost per CMAD Growth	Difference Cost per CMAD Growth	AMCS Year 3 Cost per CMAD	AMCS Year 4 Cost per CMAD	Difference Cost per CMAD	AMCS Year 3 Net Costs	AMCS Year 4 Net Costs	Difference Net Costs	AMCS Year 3 Inpatient Discharges + Outpatient Equivalent	AMCS Year 4 Inpatient Discharges + Outpatient Equivalent	Difference Inpatient Discharges + Outpatient Equivalent
2000	N/A	N/A	N/A	$ 4,882	$ 4,578	-6.2%	$ 1,396,412,115	$ 1,322,313,904	-5.3%	286,056	288,857	1.0%
2001	4.7%	9.9%	5.2%	$ 5,109	$ 5,029	-1.6%	$ 1,499,912,640	$ 1,445,092,992	-3.7%	293,585	287,346	-2.1%
2002	9.0%	9.0%	-0.1%	$ 5,571	$ 5,481	-1.6%	$ 1,683,306,851	$ 1,637,886,893	-2.7%	302,139	298,821	-1.1%
2003	3.0%	2.3%	-0.7%	$ 5,739	$ 5,608	-2.3%	$ 1,805,665,135	$ 1,758,449,304	-2.6%	314,651	313,543	-0.4%
2004	3.2%	2.9%	-0.3%	$ 5,921	$ 5,770	-2.6%	$ 1,935,873,060	$ 1,879,881,441	-2.9%	326,926	325,778	-0.4%
2005	4.0%	2.1%	-1.9%	$ 6,160	$ 5,892	-4.3%	$ 2,066,397,078	$ 1,999,436,682	-3.2%	335,440	339,331	1.2%
2006	4.2%	2.3%	-1.9%	$ 6,420	$ 6,030	-6.1%	$ 2,201,800,517	$ 2,161,304,105	-1.8%	342,978	358,418	4.5%
2007	N/A	1.2%	N/A	N/A	$ 6,102	N/A	N/A	$ 2,321,375,440	N/A	N/A	380,435	N/A

	AMCS Year 3 Outpatient Equivalent Discharges, Multiple Sources	AMCS Year 4 Outpatient Equivalent Discharges, Multiple Sources	Difference Inpatient Discharges + Outpatient Equivalent	AMCS Year 3 Case-Mix Index, MHDO	AMCS Year 4 Case-Mix Index, Multiple Sources	Difference Case-Mix Index	AMCS Year 3 Inpatient Discharges, MHDO	AMCS Year 4 Inpatient Discharges, MCRs	Difference Inpatient Discharges
2000	101,360	119,127	17.5%	1.20	1.13	-5.8%	154,445	150,609	-2.5%
2001	108,999	123,719	13.5%	1.18	1.12	-5.2%	156,120	145,928	-6.5%
2002	116,916	134,992	15.5%	1.20	1.13	-5.8%	154,976	145,467	-6.1%
2003	125,670	146,722	16.8%	1.20	1.12	-6.9%	156,895	148,722	-5.2%
2004	134,321	158,264	17.8%	1.21	1.12	-7.5%	158,667	149,265	-5.9%
2005	143,159	170,287	18.9%	1.22	1.15	-5.7%	157,459	146,865	-6.7%
2006	151,286	187,088	23.7%	1.23	1.16	-6.1%	155,668	148,166	-4.8%
2007	N/A	205,567	N/A	N/A	1.15	N/A	N/A	152,462	N/A

*Note that this comparison includes records containing data flagged as questionable or within the top or bottom 1% of calculated CMAD values so the same hospitals are compared across AMCS Years. Thus, figures presented in this table will not match those within the regression analysis.

Figure 36: Cost Reductions new in AMCS Year 4 - All States Combined

sfy	Total Costs	Swing Bed Costs	% of Total	Allowable Bad Debt Costs	% of Total
2000	$ 276,409,470,511	$ 172,519,471	0.06%	$ 701,160,843	0.25%
2001	$ 296,291,028,051	$ 186,314,895	0.07%	$ 757,901,491	0.27%
2002	$ 323,232,762,792	$ 307,311,578	0.11%	$ 945,280,089	0.34%
2003	$ 351,408,573,395	$ 407,062,823	0.15%	$ 1,034,592,552	0.37%
2004	$ 378,092,744,407	$ 503,611,629	0.18%	$ 1,117,618,790	0.40%
2005	$ 402,783,867,242	$ 592,692,832	0.21%	$ 1,227,631,881	0.44%
2006	$ 431,616,870,871	$ 717,030,662	0.26%	$ 1,265,462,469	0.46%
2007	$ 459,694,288,118	$ 839,877,758	0.30%	$ 1,377,358,070	0.50%

Figure 37: 2000/2001 Maine Discharges by Hospital by AMCS Year

									Change from 2000 to 2001					
									Absolute Amount			Percent of 2001		
	SFY	AMCS Y3	AMCS Y4	Change	SFY	AMCS Y3	AMCS Y4	Change	AMCS Y3	AMCS Y4	Change	AMCS Y3	AMCS Y4	Change
BLUE HILL MEMORIAL HOSPITAL	2000	897	664	(233)	2001	843	657	(186)	-54	-7	47	-6%	-1%	5%
BRIDGTON HOSPITAL	2000	1627	1523	(104)	2001	1587	1494	(93)	-40	-29	11	-3%	-2%	1%
CALAIS REGIONAL HOSPITAL	2000	1145	1131	(14)	2001	1106	1128	22	-39	-3	36	-4%	0%	3%
CARY MEDICAL CENTER	2000	2475	2245	(230)	2001	2428	2292	(136)	-47	47	94	-2%	2%	4%
CENTRAL MAINE MEDICAL CENTER	2000	8585	9414	829	2001	8058	8085	27	-527	-1329	-802	-7%	-16%	-10%
CHARLES A DEAN MEMORIAL HOSPITAL	2000	278	237	(41)	2001	210	208	(2)	-68	-29	39	-32%	-14%	18%
DOWN EAST COMMUNITY HOSPITAL	2000	1663	1593	(70)	2001	1687	1645	(42)	24	52	28	1%	3%	2%

	SFY	AMCS Y3	AMCS Y4	Change	SFY	AMCS Y3	AMCS Y4	Change	AMCS Y3	AMCS Y4	Change	AMCS Y3	AMCS Y4	Change
EASTERN MAINE MEDICAL CENTER	2000	17973	18233	260	2001	18156	16581	(1,575)	183	-1651	-1834	1%	-10%	-11%
FRANKLIN MEMORIAL HOSPITAL	2000	2793	2836	43	2001	2741	3043	302	-52	207	259	-2%	7%	9%
H.D. GOODALL HOSPITAL	2000	2049	1815	(234)	2001	2306	1554	(752)	257	-260	-517	11%	-17%	-28%
HOULTON REGIONAL HOSPITAL	2000	1763	1911	148	2001	1885	1933	48	122	22	-100	6%	1%	-5%
INLAND HOSPITAL	2000	2006	1763	(243)	2001	2242	2001	(241)	236	238	2	11%	12%	1%
MAINE COAST MEMORIAL HOSPITAL	2000	2556	2535	(21)	2001	2715	2743	28	159	208	49	6%	8%	2%
MAINE MEDICAL CENTER	2000	30544	30564	20	2001	30702	29384	(1,318)	158	-1180	-1338	1%	-4%	-5%
MAINEGENERAL MEDICAL CENTER	2000	13412	12221	(1,191)	2001	14087	12328	(1,759)	675	107	-568	5%	1%	-4%

	SFY	AMCS Y3	AMCS Y4	Change	SFY	AMCS Y3	AMCS Y4	Change	AMCS Y3	AMCS Y4	Change	AMCS Y3	AMCS Y4	Change
MAYO REGIONAL HOSPITAL	2000	1822	1681	(141)	2001	1834	1674	(160)	12	-7	-19	1%	0%	-1%
MERCY HOSPITAL	2000	10595	10585	(10)	2001	10564	10098	(466)	-31	-487	-456	0%	-5%	-5%
MID COAST HOSPITAL	2000	4281	4309	28	2001	4407	4463	56	126	154	28	3%	3%	1%
MILES MEMORIAL HOSPITAL	2000	2005	2050	45	2001	2003	2047	44	-2	-4	-2	0%	0%	0%
MILLINOCKET REGIONAL HOSPITAL	2000	943	889	(54)	2001	1008	925	(83)	65	36	-29	6%	4%	-3%
MOUNT DESERT ISLAND HOSPITAL	2000	1409	1158	(251)	2001	1599	806	(793)	190	-352	-542	12%	-44%	-55%
NORTHERN MAINE MEDICAL CENTER	2000	1613	1641	28	2001	1690	1852	162	77	211	134	5%	11%	7%
PARKVIEW ADVENTIST MEDICAL CENTER	2000	2546	2327	(219)	2001	2524	2318	(206)	-22	-9	13	-1%	0%	0%

	SFY	AMCS Y3	AMCS Y4	Change	SFY	AMCS Y3	AMCS Y4	Change	AMCS Y3	AMCS Y4	Change	AMCS Y3	AMCS Y4	Change
PENOBSCOT BAY MEDICAL CENTER	2000	4970	4651	(319)	2001	4896	4580	(316)	-74	-71	3	-2%	-2%	0%
PENOBSCOT VALLEY HOSPITAL	2000	1096	835	(261)	2001	1061	661	(400)	-35	-173	-138	-3%	-26%	-23%
REDINGTON-FAIRVIEW GENERAL HOSPITAL	2000	2491	2252	(239)	2001	2354	2151	(203)	-137	-101	36	-6%	-5%	1%
RUMFORD COMMUNITY HOSPITAL	2000	1298	1298	-	2001	1285	1292	7	-13	-6	7	-1%	0%	1%
SEBASTICOOK VALLEY HOSPITAL	2000	1365	1399	34	2001	1148	1197	49	-217	-202	15	-19%	-17%	2%
SOUTHERN MAINE MEDICAL CENTER	2000	6087	6095	8	2001	6001	6012	11	-86	-83	3	-1%	-1%	0%
ST ANDREWS HOSPITAL	2000	309	267	(42)	2001	308	311	3	-1	44	45	0%	14%	14%
ST. JOSEPH HOSPITAL	2000	3939	3770	(169)	2001	3995	3998	3	56	228	172	1%	6%	4%

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	SFY	AMCS Y3	AMCS Y4	Change	SFY	AMCS Y3	AMCS Y4	Change	AMCS Y3	AMCS Y4	Change	AMCS Y3	AMCS Y4	Change
ST. MARY S REGIONAL MEDICAL CENTER	2000	6468	6340	(128)	2001	6752	6119	(633)	284	-220	-504	4%	-4%	-8%
STEPHENS MEMORIAL HOSPITAL	2000	2139	1704	(435)	2001	2197	2043	(154)	58	339	281	3%	17%	14%
THE AROOSTOOK MEDICAL CENTER	2000	3294	2827	(467)	2001	3196	2888	(308)	-98	61	159	-3%	2%	5%
WALDO COUNTY GENERAL HOSPITAL	2000	2222	2001	(221)	2001	2444	2235	(209)	222	234	12	9%	10%	1%
YORK HOSPITAL	2000	3787	3846	59	2001	4104	3180	(924)	317	-666	-983	8%	-21%	-29%

Total	2000	154445	150609	-3836	2001	156123	145928	-10195	1678	-4681	6359	1%	-3%	4%

APPENDIX F: CMAD DATA SCRUBBING SUMMARY

The data validation process was conducted in a tiered manner which varies according to the use of the data in question. Fields were first classified as to whether or not they were relevant at the CMAD calculation or regression level. Differing steps were taken to verify data in each of these types of fields.

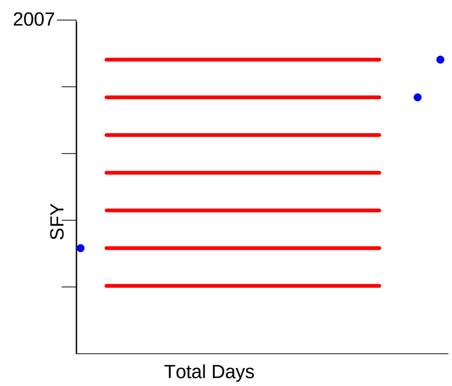
Calculation-level data: Data that is used to compute the value of cost per Case-Mix and outpatient adjusted discharge (CMAD) is considered calculation-level data. This consists of variables such as Total Costs, Nursing Facility Costs, and Inpatient Discharges. A wide range of values is plausible for computation data, so records are only removed if they are missing one of the components essential to the calculation. These essential components are Total Costs, Inpatient Discharges, Total Gross Patient Service Revenue, Gross Inpatient Service Revenue, and Case-Mix Index. In addition to these variables, only records with positive values for days and beds are kept. This is because it is counterintuitive to have a hospital claim costs and discharges despite having no recorded days or beds. As a final check for overall reasonableness, the top and bottom percentile of CMAD values were flagged for removal. This ensures that no hospital with reasonable values for all calculation data but an exceedingly large or small CMAD value influences the savings calculation. Figure 38 illustrates the data scrubbing performed for calculation-level data.

Figure 38: Data missing essential calculation variables.
In this example record numbers 1 and 2 would be kept but
record number 3 would be removed.

Rec #	PRVDR_ NUM	Beds	NF Costs	Inpatient Discharges	Total Costs	Inpatient GPSR	Total GPSR	SNF Costs
1	250093	133		6120	38143992	82065891	146669860	1535374
2	330033	58		1709	33299995	27182927	85131805	5312277
3	010145	196		9983	53175872			

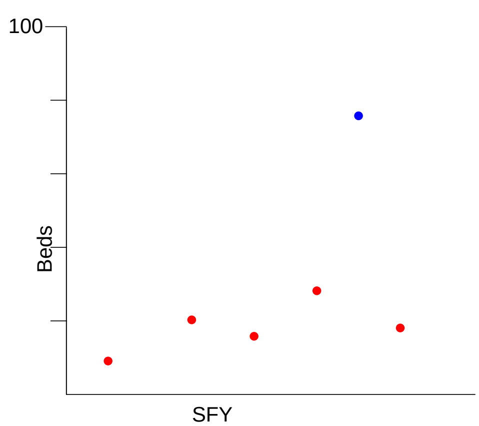
Regression-level data: Regression-level data is data that is not used in the calculation; rather, it is used as an independent variable in the regression analysis. The variables used for regression data include Beds, Total Days, and an Urban/Rural Indicator and others. The first check that was performed on these variables screened for any outliers on a total magnitude level based on their relationship to similar variables in the data set. The data was arrayed linearly across all hospital/year records by each variable to see if any extreme outliers existed, as Figure 39 shows.

Figure 39: The data is arrayed linearly by a specific variable to check for extreme outliers. In this case the blue dots would be considered outliers.



Highest and lowest reasonable points were determined as reasonable boundary values based on this analysis, and all records with values outside of these boundaries were removed. The variables also should be comparable from year to year for an individual hospital, and while a comprehensive check of every variable for every hospital is not feasible due to the size of the data set, several spot checks were conducted. For the spot checks, an entire hospital's experience for a specific variable was graphed, as in Figure 40 below.

Figure 40: A single hospital's experience for a specific variable is graphed. In this example, the year corresponding to the blue dot would be investigated to determine reasonableness.



The graph was then checked for outliers. Once a potential outlier was identified, the hospital's Medicare Cost Report (MCR) was consulted to verify that the number was extracted correctly and to see if the number was clearly an entry error by the hospital. If it could be determined that the value was an erroneous entry, then the record was removed. If not, an extensive review of the hospital's previous and subsequent MCRs was conducted to see if the extraneous value could be reasonable. If the value was reasonable in the context of the hospital's growth trends and operating condition the record was kept, while if the value was unreasonable the record was removed. The final check that was conducted to ensure reasonableness among the regression variables was an arithmetic check. Certain values should be smaller than others, for example Medicare days and Medicaid days should each be less than Total Days. Several similar arithmetic checks similar to Figure 41 below were conducted to ensure that the data was not contradictory and contained reasonable values. These additional reasonableness checks are detailed as follows:

- If any variable was below zero it was flagged for removal.
- The number of interns and residents was capped at 1330 due to a verified outlier.
- Discharges were checked to verify Medicare and Medicaid discharges were each less than total discharges and that the sum of Medicare and Medicaid discharges was less than total discharges. Discharges were also capped at 109000 due to a verified outlier.
- Gross Inpatient Service Revenue was checked to make sure it is less than Total Gross Patient Service Revenue.
- Indicator variables telling whether a hospital is in Maine or a critical access hospital were checked for values greater than 1.

Figure 41: Record number 2 would be removed because Total Days is less than Medicare Days, and record number 3 would be removed because the sum of Medicare and Medicaid Days is greater than Total Days

Record Number	PRVDR_NUM	Beds	Medicare Days	Medicaid Days	Total Days
1	170101	37.99	984.08	37.24	1401.47
2	200023	14.9	666.75	16.96	543.54
3	111319	25	617.72	447.62	867.9

When performing the regression analysis, we removed all records that had been incomplete at the calculation level, flagged as questionable or included within the top and bottom one percent of the calculated CMAD values. The check for vital calculation level data removes less than 2.5% of records matching the criteria of the analysis (correct time period and provider type). The check for questionable regression data removes a very small amount of records (< 20), and the check of the top and bottom percent of CMAD values removes approximately 2% of the records.

This amounts to the removal of less than 5% of the total eligible records. For more details on the number of records removed in various steps of the calculation, see SAS Code Descriptions.xls, |Records Removed-Step by Step| tab.

APPENDIX G: CMAD ANALYSIS SENSITIVITY TO MODEL ASSUMPTIONS

Technical Appendix

The purpose of this Technical Appendix is to examine the sensitivity of the results to the different analytic decisions that were made in the analysis. The results presented in the main text represent what we believe to be the best model, both theoretically and empirically. However, in the interest of completeness, we are including results demonstrating the effect of the different assumptions on the results.

There were seven key categories of decisions that were made that could plausibly affect the outcomes of the analysis: 1) the use of the logged dependent variable, 2) dealing with "questionable" observations, 3) the use of fixed effects models, 4) collinearity issues, 5) the use of year as a continuous variable rather than a fixed effect, 6) the inclusion of county level variables, and 7) the alternative of a random effects model. We find that none of these decisions made a substantive effect on the overall results, although the statistical significance of the results did vary somewhat, with superior performance found in our preferred model. The Dirigo effect was very similar in all models, except the model without hospital level fixed effects. The R^2 was quite high in all specifications, again excepting the model without hospital level fixed effects. The model without hospital level fixed effects performed significantly worse.

Figure 42: Summary of Sensitivity Analysis

Model	Dirigo Effect[57]	P value	Model R^2	Figure
Baseline	-.0367	.046	0.8949	44
1. Non-Logged Dependent Variable	-196.98	.089	0.8792	45
2. Including Questionable Observations	-.0399	.046	0.8947	48
3. No Hospital Fixed Effects	.005	.833	0.1720	49
4. Collinearity Issues	-.0618	.002	0.8948	50
5. Hospital and Year Fixed Effects	-.0367	.046	0.8951	51
6. Including Community Characteristics	-.0362	.049	0.8951	52
7. Random Effects Model	-0.067	<.001	0.1280	53

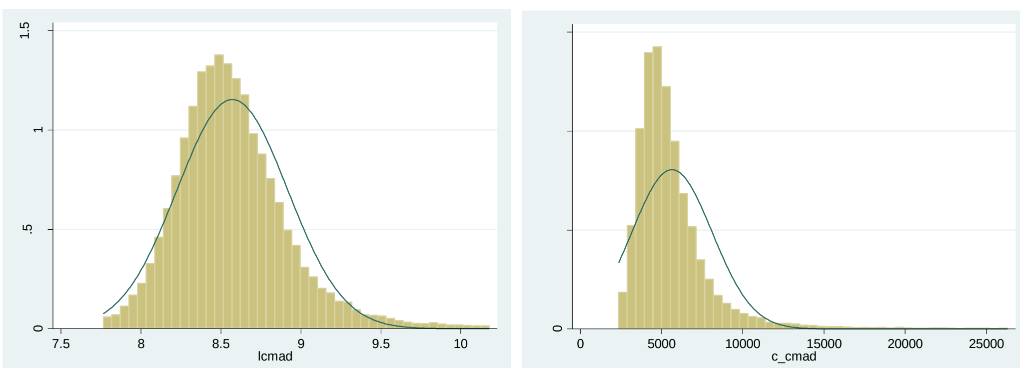
[57] Indicator variables related to logged dependent variables, except as noted.

1. The Use of Logged Dependent Variables

The use of logged dependent variables is relatively common in econometrics. Ordinary Least Squares (OLS) regressions such as those used in this analysis assume a linear relationship between the dependent and independent variables. In some circumstances, a linear relationship can be more precisely estimated if the dependent variable is transformed to an alternate scale, such as taking a log.

Figure 43 presents a comparison of the logged dependent variable (on the left) and the unlogged dependent variable. The logged dependent variable is approximately normal, while the unlogged dependent variable is not at all normal, with too high a "peak" and a long "tail" of observations to the right. Normality of the dependent variable is not necessary for the OLS model, however, normality of the residuals is a requirement for inference. When the dependent variable is more normal, that often leads to superior properties of the residuals.

Figure 43: Comparison of CMAD and Logged CMAD with Normal Curve



In more formal tests, we find that the skewness of the unlogged dependent variable is equal to 3.05 (indicating the peak) while the kurtosis is very non-normal at 17.72. In contrast, the logged dependent variable is more nearly normal, with a skewness of 0.921 and a Kurtosis of 4.87.

Comparing the results of the base regression with logged dependent variable (Figure 44) to that with unlogged dependent variables (Figure 45), the substantive results are quite similar, although the model fit is better for the model with the logged dependent variable.

For the "Dirigo Effect", the unlogged dependent variable finds that Dirigo decreased CMAD by an average of $197 on average across all Dirigo years and that the result was borderline statistically significant (p=0.089). For the logged dependent variable, the coefficient is again negative (β=-.0367) and statistically significant (p=.046). Translating the coefficient into a percentage change, as in the main text $((e^{-0.0367}-1)*100)$, we find that this suggests that Dirigo decreased spending by 3.6%, or an average cost of 223 in 2007. So the results of the two models are substantively similar.

Overall, the logged model performs significantly better. The R^2 for the unlogged model is 0.879, while the R^2 for the logged model is 0.895. Similarly, the F statistic is slightly greater for the logged model (1109 for the unlogged model versus 1895). Also, most of the variables are more statistically significant in the logged model, reflecting its better overall fit.

Figure 44: Fixed Effects Regression with Logged Dependent Variable

Linear regression, absorbing indicators

Number of obs = 35383
F(9, 29388) = 1894.78
Prob > F = 0.0000
R-squared = 0.8949
Adj R-squared = 0.8735
Root MSE = .12303

c_cmad	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
dirigoyr	-.001145	.0025526	-0.45	0.654	-.0061482	.0038582
difdif	-.0367259	.0183728	-2.00	0.046	-.0727373	-.0007144
pctday_caid	-.0370032	.0302839	-1.22	0.222	-.096361	.0223545
pctday_care	.3605067	.0266331	13.54	0.000	.3083048	.4127087
int_res	-.0002334	.0000834	-2.80	0.005	-.0003969	-.0000699
trans	-.1883444	.0682725	-2.76	0.006	-.3221616	-.0545273
critcare	.0489291	.0466266	1.05	0.294	-.0424611	.1403193
beds	.0000601	.0000363	1.66	0.098	-.000011	.0001313
sfy	.0459841	.000639	71.96	0.000	.0447316	.0472366
_cons	-83.72796	1.278677	-65.48	0.000	-86.23423	-81.2217
Hospital Fixed Effects			absorbed		(5986 categories)	

Figure 45: Fixed Effects Regression with Unlogged Dependent Variable

Linear regression, absorbing indicators

Number of obs = 35383
F(9, 29388) = 1109.05
Prob > F = 0.0000
R-squared = 0.8792
Adj R-squared = 0.8546
Root MSE = 945.17

c_cmad	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
dirigoyr	-3.537465	19.46759	-0.18	0.856	-41.69481	34.61988
difdif	-196.9755	115.997	-1.70	0.089	-424.3349	30.38384
pctday_caid	-689.6949	246.4131	-2.80	0.005	-1172.676	-206.7143
pctday_care	2267.786	229.5863	9.88	0.000	1817.787	2717.786
int_res	.0503105	.7313813	0.07	0.945	-1.383229	1.48385
trans	-1247.008	383.9579	-3.25	0.001	-1999.583	-494.4336
critcare	497.9925	403.3308	1.23	0.217	-292.5538	1288.539
beds	-.3698836	.2932407	-1.26	0.207	-.9446485	.2048814
sfy	262.1251	4.872005	53.80	0.000	252.5757	271.6744
_cons	-520451.5	9744.116	-53.41	0.000	-539550.4	-501352.6
Hospital Fixed Effects			absorbed		(5986 categories)	

2. "Questionable" observations

As discussed in great detail in the main text, there are two different types of observations that are considered "questionable". In the main results, we removed all observations that were either above or below the 1% line plus observations that exhibited unlikely year-to-year changes. This change affected five observations in Maine in the data, two in the year 2000, one in 2001 (one hospital was excluded in both 2000 and 2001) and two others in 2005. This left 34 observations in 2000 and 2005, 35 in 2001 and 36 in all other years.

Figure 46 presents three different scenarios for including or excluding the questionable data. The first two columns shows mean expenditures as the sample was created for the analysis: observations were excluded only if they were questionable for that given year. The second two columns show mean expenditures if we exclude the two questionable hospitals for all years and the final two columns shows mean expenditures if we include the two questionable hospitals for all years.

The hospitals have the effect of increasing mean CMAD slightly in 2000 (from $4,618 to $4,627), increasing mean CMAD slightly in 2001 ($5,055 for 34 hospitals versus $5,082 for 32 hospitals) and in subsequent years. Comparing the data we used (excluding observations by year) versus the data with all observations, the only differences would be for 2000, 2001 and 2005. The middle column – depicting the data with only 32 hospitals – does not seem a reasonable option because it throws away five hospitals for no compelling reason. Thus we will compare the effect of a) including all Maine hospitals but excluding questionable hospitals from other states and b) including all hospitals. Our reference regression will be the regression with a logged dependent variable given in Figure 44.

Figure 46: Mean CMAD for Maine Hospitals with and without Questionable Observations

Fiscal Year	Removing Questionable Observations by Year		Removing Questionable Hospitals for All Years		All Hospitals for All Years	
	Observations	Mean CMAD	Observations	Mean CMAD	Observations	Mean CMAD
2000	34	4599	32	4608	36	4578
2001	35	5022	32	5052	36	5029
2002	36	5481	32	5510	36	5481
2003	36	5608	32	5653	36	5608
2004	36	5770	32	5817	36	5770
2005	34	5993	32	6009	36	5892
2006	36	6030	32	6117	36	6030
2007	36	6102	32	6224	36	6102

Overall, the results are quite similar for the sample with all Maine hospitals (Figure 47) versus that excluding the hospitals with questionable observations in Maine (Figure 44). The sample size in Figure 47 (35,388) shows that the five extra hospital / year observations were included (versus 35,383). The model fit is very similar, with an R^2 of 0.8949 in the base model versus 0.8947 in the model with all data. The Dirigo Effect coefficient is statistically significant in both models (p=0.046 in the base model versus p=0.046 in the model with all data). The coefficient is negative in both models and overall substantively similar (β=-.0367 versus β=-.0399).

Figure 47: Fixed Effects Regression, Logged Dependent Variable, Including Questionable Maine Hospitals

Linear regression, absorbing indicators

Number of obs = 35388
F(9, 29393) = 1893.57
Prob > F = 0.0000
R-squared = 0.8947
Adj R-squared = 0.8732
Root MSE = .12317

lcmad	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
dirigoyr	-.0012511	.0025534	-0.49	0.624	-.006256	.0037537
difdif	-.0399529	.0200408	-1.99	0.046	-.0792338	-.0006719
pctday_caid	-.0380158	.0303158	-1.25	0.210	-.0974361	.0214045
pctday_care	.3559722	.0267823	13.29	0.000	.3034777	.4084667
int_res	-.0002335	.0000834	-2.80	0.005	-.000397	-.00007
trans	-.1687502	.070278	-2.40	0.016	-.3064982	-.0310023
critcare	.0597455	.04708	1.27	0.204	-.0325335	.1520244
beds	.0000604	.0000363	1.66	0.096	-.0000108	.0001316
sfy	.046009	.0006392	71.98	0.000	.0447561	.0472619
_cons	-83.77983	1.279103	-65.50	0.000	-86.28693	-81.27273
Hospital Fixed Effects			absorbed			(5986 categories)

Similarly, the results are also consistent if we include all hospitals (Figure 48) versus that excluding the hospitals with questionable observations in Maine (Figure 44) and that excluding only Maine hospitals with questionable observations. The sample size in Figure 48 (36,121) shows that the 738 extra hospital / year observations were included (versus the 35,383). The model fit is again very similar, with an R^2 of 0.8949 in the base model versus 0.8968 in the model with all data. The Dirigo Effect coefficient is statistically significant in both models (p=0.046 in the base model versus p=0.034 in the model with all data). The coefficient is negative in all models, with the coefficient in the model with all data (β=-.0425) slightly larger than the reduced model (β=-.0367).

Figure 48: Fixed Effects Regression, Logged Dependent Variable, Including All Questionable Observations

Linear regression, absorbing indicators

Number of obs = 36121
F(9, 30059) = 1224.33
Prob > F = 0.0000
R-squared = 0.8968
Adj R-squared = 0.8760
Root MSE = .15819

lcmad	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
dirigoyr	-.0023573	.0032635	-0.72	0.470	-.0087539	.0040393
difdif	-.0424565	.0200622	-2.12	0.034	-.0817793	-.0031336
pctday_caid	-.0077201	.0916909	-0.08	0.933	-.1874382	.171998
pctday_care	.2807989	.0432851	6.49	0.000	.1959582	.3656395
int_res	1.44e-06	1.94e-06	0.74	0.457	-2.36e-06	5.24e-06
trans	-.1594273	.0728676	-2.19	0.029	-.302251	-.0166036
critcare	.0377165	.0535391	0.70	0.481	-.0672224	.1426554
beds	-.0000135	.0000414	-0.33	0.744	-.0000947	.0000676
sfy	.0470259	.0008885	52.93	0.000	.0452844	.0487674
_cons	-85.76021	1.777736	-48.24	0.000	-89.24465	-82.27577
Hospital Fixed Effects			absorbed			(6053 categories)

Overall, we find no evidence that our results are dependent in any way on the inclusion or exclusion of questionable hospital observations. We prefer our base model because 1) it is in keeping with standard practices in the analysis of CMAD data and 2) the exclusion of extreme values makes the analysis more representative of the "typical" hospital. However, the results are similar across all specifications.

3. The use of fixed effects models

In our models, we used a "fixed effects" specification. This specification includes an intercept shift of each individual hospital. This approach creates, in effect, a hospital specific effect. Is this approach necessary? Figure 49 provides the result of an OLS regression, without fixed effects.

This model is inferior to the Fixed Effects model. The R^2 is 0.172, suggesting that the regression as specified explains approximately 17.2% of the variance in the dependent variable. This is in contrast to the Fixed Effects Model which has an R^2=.8949. A formal test of the appropriateness of the fixed effects model is:

$$F = \frac{R_{ur}^2 - R_r^2 / m}{1 - R_{ur}^2 / n - k}$$

Where R^2_{ur} is the R^2 from the unrestricted (fixed effects) model, R^2 is the R^2 from the restricted (OLS) model (where all the intercepts are restricted to be identical), m represents the number of restrictions (in this case, 6,051 intercepts are constrained to be identical) n is the sample size and k is the number of parameters in the unrestricted regression.[58] The F statistic in this example is equal to 33.41 and highly significant, so we therefore reject the restricted model.

Figure 49: OLS Regression, Logged Dependent Variable

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    Source |       SS       df       MS              Number of obs =   35383
-------------+------------------------------         F(  9, 35373) =  816.58
     Model |  728.081165     9    80.8979073         Prob > F      =  0.0000
  Residual |  3504.38086 35373  .099069371           R-squared     =  0.1720
-------------+------------------------------         Adj R-squared =  0.1718
     Total |  4232.46202  35382  .119621899          Root MSE      =  .31475
```

cmad	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]
dirigoyr	.0078238	.0068613	1.14	0.254	-.0056245 .0212721
difdif	.0056196	.0266273	0.21	0.833	-.0465707 .0578099
pctday_caid	-.3107423	.0184163	-16.87	0.000	-.3468388 -.2746458
pctday_care	-.1617821	.0132538	-12.21	0.000	-.18776 -.1358042
int_res	.0007458	.0000312	23.87	0.000	.0006846 .0008071
trans	.1723331	.0520062	3.31	0.001	.0703994 .2742668
critcare	.0579246	.0521336	1.11	0.267	-.0442588 .160108
beds	.0001577	.0000133	11.88	0.000	.0001317 .0001837
sfy	.035908	.0015081	23.81	0.000	.032952 .038864
_cons	-63.31579	3.018711	-20.97	0.000	-69.23255 -57.39902

4. Inclusion of Variables Measuring Critical Access Hospitals and Issues of Collinearity

One issue is whether to include measures of critical access hospitals in the model. The critical access hospital variables are potentially very collinear with the fixed effects. When variables that are too highly correlated are included in a regression model of this type (termed "multicollinearity"), it will cause the standard errors to become inflated and may cause the estimated coefficients to become unstable. There are different schools of thought on how to test for and measure multicollinearity.

One school of thought suggests a series of benchmarks to indicate multicollinearity is a problem. Suggestions often include correlations over 0.90 or Variance Inflation Factors ("VIF") over 5. An

[58] From Chapter 16 of "Basic Econometrics" by Damodar N. Gujarati.

alternative suggests that multicollinearity is only a problem if the coefficients become unstable (i.e. have implausible magnitudes) or standard errors seem unreasonable large.

The VIF for these two variables indicates a potential problem with multicollinearity. The VIF for the transition variable is 121.00, while the VIF for the critical access indicator is 120.88. However, the two variables are statistically significant in the model and the R^2 in the model is similar (0.8948 versus 0.8949). However, the coefficient measuring the effect of Dirigo is negative and statistically significant in both cases (-0.0618 in the expanded model versus -0.0367 with similar levels of statistical significance), suggesting collinearity is not a particular problem in this model.

Figure 50: Fixed Effects Regression, Logged Dependent Variable Excluding Measures of Critical Access Hospitals

Linear regression, absorbing indicators

Number of obs = 35383
F(7, 29390) = 2428.41
Prob > F = 0.0000
R-squared = 0.8948
Adj R-squared = 0.8733
Root MSE = .12309

lcmad	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
dirigoyr	-.0009605	.0025547	-0.38	0.707	-.0059678	.0040468
difdif	-.0617572	.0197817	-3.12	0.002	-.1005302	-.0229842
pctday_caid	-.038131	.0303414	-1.26	0.209	-.0976014	.0213394
pctday_care	.3624481	.0266043	13.62	0.000	.3103024	.4145937
int_res	-.0002334	.0000835	-2.80	0.005	-.0003971	-.0000698
beds	.0000636	.0000364	1.75	0.081	-7.75e-06	.0001349
sfy	.0459544	.0006396	71.85	0.000	.0447007	.047208
_cons	-83.69039	1.280116	-65.38	0.000	-86.19948	-81.18131
Hospital Fixed Effects			absorbed			(5986 categories)

5. The Use of Year as a Continuous Variable Rather than a Fixed Effect.

In our model, we included "year" as a continuous variable rather than as a "fixed effect". A fixed effect approach would include indicator variables for each year rather than a smoothed annual effect. The advantage of the fixed effects approach is that it allows the year-to-year changes to vary, while including year as a continuous variable forces the year-to-year changes to be identical – the β when using a continuous variable represents the average annual change over all years. The advantage of the continuous variable approach is that there is a problem with perfect multicollinearity when including fixed effects for years and the Dirigo Year variable[59]. So,

[59] Perfect multicollinearity refers to a situation where two variables (or combinations of variables) are exactly equal to one another. In this case, adding up the post-Dirigo indicator

to include yearly fixed effects, we were required to drop the Dirigo indicator variable. However, the indicator variables for the post-Dirigo years serve the same role.

We find that there is little gain to including yearly fixed effects (Figure 51). The fit of the model is not improved (R^2 of 0.8951 versus 0.8949) and the Dirigo effect coefficient is virtually unchanged (-0.036716 versus -0.036726). Looking at the coefficients on the years, the effect is approximately linear[60], which suggests that using a linear time trend is appropriate.

Figure 51: Fixed Effects Regression, Logged Dependent Variable with Yearly Fixed Effects

Linear regression, absorbing indicators

Number of obs = 35383
F(14, 29383) = 1244.63
Prob > F = 0.0000
R-squared = 0.8951
Adj R-squared = 0.8737
Root MSE = .12291

lcmad	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
difdif	-.036716	.0183954	-2.00	0.046	-.0727717	-.0006602
pctday_caid	-.0563996	.0307112	-1.84	0.066	-.116595	.0037958
pctday_care	.3475748	.0271847	12.79	0.000	.2942915	.400858
int_res	-.0002328	.0000837	-2.78	0.005	-.0003969	-.0000688
trans	-.1873172	.0684715	-2.74	0.006	-.3215244	-.05311
Critcare	.0489922	.0466498	1.05	0.294	-.0424436	.1404279
beds	.000059	.0000365	1.62	0.106	-.0000125	.0001305
y2001	.0360676	.0028597	12.61	0.000	.0304625	.0416727
y2002	.0877941	.0029533	29.73	0.000	.0820054	.0935828
y2003	.1459962	.0029129	50.12	0.000	.1402868	.1517056
y2004	.1866523	.0029002	64.36	0.000	.1809678	.1923369
y2005	.2274084	.0030103	75.54	0.000	.2215082	.2333087
y2006	.2739402	.0031283	87.57	0.000	.2678085	.2800718
y2007	.3148472	.0033336	94.45	0.000	.3083131	.3213813
cons	8.251241	.0194409	424.43	0.000	8.213136	8.289346
Hospital Fixed Effects			absorbed		(5986 categories)	

variables would be exactly equal to the Dirigo variable. In this situation, it is not mathematically possible to estimate a regression coefficient.

[60] The coefficients should be interpreted as changes relative to the reference year, 2000.

6. Including Measures of Community Characteristics.

We also examined including measures of community characteristics in our model (see Figure 52). The difficulty is that the fixed effects at the hospital level absorb any time invariant community characteristics and most community characteristics do not vary substantially over the relatively short time frame we're examining.

In this model, we include several measures of community characteristics. These include median county income, the county population and the mean unemployment rate in the county. Combined, these variables explain little of the variance in CMAD and have little effect on the estimated Dirigo effect or the statistical significance of Dirigo (R-squared is virtually unchanged).

Figure 52: Inclusion of Community Variables

Linear regression, absorbing indicators

Number of obs = 35383
F(12, 29385) = 1443.10
Prob > F = 0.0000
R-squared = 0.8951
Adj R-squared = 0.8737
Root MSE = .12291

lcmad	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
dirigoyr	-.0009106	.0026308	-0.35	0.729	-.0060672	.004246
difdif	-.0361791	.0183795	-1.97	0.049	-.0722037	-.0001545
pctday_caid	-.0533152	.0307216	-1.74	0.083	-.113531	.0069005
pctday_care	.3513027	.0268889	13.06	0.000	.2985993	.4040061
int_res	-.0002276	.0000838	-2.72	0.007	-.0003919	-.0000633
trans	-.191275	.0680871	-2.81	0.005	-.3247288	-.0578212
critcare	.0543263	.0464941	1.17	0.243	-.0368042	.1454569
beds	.0000494	.0000362	1.37	0.172	-.0000215	.0001204
sfy	.0456189	.0006589	69.24	0.000	.0443275	.0469103
cnty_mincome	7.15e-06	1.92e-06	3.72	0.000	3.38e-06	.0000109
cnty_pop	1.61e-07	2.44e-08	6.59	0.000	1.13e-07	2.09e-07
cnty_ur	.0018564	.0009129	2.03	0.042	.000067	.0036458
_cons	-83.37478	1.327687	-62.80	0.000	-85.9771	-80.77245
Hospital Fixed Effects			absorbed			(5986 categories)

7. Random Effect Models.

The random effects model is a different way of modeling the hospital specific differences than the fixed effects model. Instead of treating the intercept as fixed over time, it is assumed to be a random variable with a mean value equal for all hospitals and a distribution which leads different hospitals to have different values. The error term in the equation thus has two components, individual specific portion and a combined time series and cross sectional component.

There are two key advantages to the random effects model. First, because it does not fit a hospital specific intercept term, it uses up far fewer degrees of freedom. Second, the random effects model allows for the estimation of time invariant variables. However, for this analysis, neither of these advantages is particularly advantageous – we have sufficient degrees of freedom for the random effects model and we do not have any time invariant characteristics.

The random effects model also has one critical assumption. It assumes that the (unobserved) error term is uncorrelated with all of the control variables. This is a very strong assumption and is rarely realistic.

We estimated a random effects model (see Figure 53). In this model, the Dirigo effect is substantially large (β=-0.067) and strongly statistically significant (p<.001). This corresponds to a 6.48% Dirigo effect, substantially larger than the estimate from the fixed effects model.

Figure 53: Random Effects Model

Random-effects GLS regression	Number of obs = 35383
Group variable: prvdr_num	Number of groups = 5986
R-sq: within = 0.4112	Obs per group: min = 1
Between = 0.0412	avg = 5.9
overall = 0.1276	max= 12
Random effects u_i ~ Gaussian	Wald chi2(9) = 18780.57
corr(u_i, X) = 0 (assumed)	Prob > chi2 = 0.0000

(Std. Err. adjusted for clustering on prvdr_num)

lcmad	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
dirigoyr	.0008252	.0025524	0.32	0.746	-.0041773	.0058278
difdif	-.0671242	.0181922	-3.69	0.000	-.1027802	-.0314682
pctday_caid	-.086096	.0262107	-3.28	0.001	-.137468	-.034724
pctday_care	.2490941	.0218631	11.39	0.000	.2062432	.291945
int_res	.0003989	.0000587	6.80	0.000	.0002839	.0005139
beds	.0001387	.0000237	5.85	0.000	.0000922	.0001852
sfy	.0450053	.0006192	72.68	0.000	.0437917	.046219
critcare	.0882215	.0478964	1.84	0.065	-.0056537	.1820966
trans	-.0203143	.0493136	-0.41	0.680	-.1169673	.0763386
cons	-81.7439	1.238994	-65.98	0.000	-84.17229	-79.31552

Random Effects
sigma_u .31778956
sigma_e .12302962
rho .8696569 (fraction of variance due to u_i)

However, we reject this model in favor of the fixed effects model for three reasons. First, we consider the assumption that this error term is uncorrelated to the control variables particularly untenable in this application. Second, the model fit is inferior (R^2 of 0.128 in the random effect model versus 0.8949 in the fixed effects model). Third, a Hausman specification test rejected the random effects model in favor of a fixed effects model ($\chi^2(9)=107.89$, $p<.001$)

APPENDIX H: CMAD IMPACT OF INPATIENT TO OUTPATIENT SHIFT

Effect of Increased Outpatient Volume on CMAD Calculation

CMAD Formula Component	Impact	Rationale	Effect on Calculated CMAD	Effect on Savings
Hospital Only Expenses	?	A shift from inpatient to outpatient services will definitely increase outpatient costs. What is not known, though, is the magnitude of the decrease to inpatient costs. The net total cost figure could go up, down, or stay the same in response to the increased outpatient volume.	?	?
Bad Debt	?	An increase to outpatient volume should not affect, on a percent basis, the amount of bad debt reported.	?	?
Hospital Tax	↔	Regardless of whether or not the increased outpatient volume increased the tax amount, the tax is netted out in the calculation of CMAD. There will be no effect.	↔	↔
Inpatient Discharges	↓	Depending on the degree to which inpatient volume drops in response to an increase in outpatient volume, this figure could stay the same or go down. It is most likely the number of discharges will decrease to some degree.	↑	↓
Case-Mix Index	↑	Because the CMI is calculated only off of inpatient experience, a shift from inpatient to outpatient services should transfer the less severe inpatient cases over to an outpatient setting. This would result in an increase to the calculated CMI.	↓	↑
Outpatient Volume Adjustor	↑	The outpatient volume adjustment looks at revenue from both inpatient and outpatient services. Should both of these increase relatively the same, then the ratio would be unaffected. Most likely, the revenue for outpatient services would increase and the revenue for inpatient services would decrease. This would cause the volume adjustment factor to increase.	↓	↑

Summary
Any increase in outpatient utilization will have multiple, conditional effects on the calculated cost per CMAD. The resulting impact would depend on the level to which inpatient services were shifted to an outpatient setting and the relative costs of those services. Because the true impact of this hypothesized issue is indeterminate and not measurable, the fixed-effects in the regression methodology most appropriately control for this issue.

APPENDIX I: CMAD IMPACT OF MAINECARE REIMBURSEMENT

Effect of Lower Increase in MaineCare Revenue on CMAD Calculation

CMAD Formula Component	Impact	Rationale	Effect on Calculated CMAD	Effect on Savings
Hospital Only Expenses	?	The response a hospital would have to a reduction in the annual MaineCare reimbursement increases is indeterminate at the total cost level. The lower levels of reimbursement could be absorbed by the hospital, offset by a reduction in costs, or offset by an increase to charges. Because the decrease is actually a reduction to an expected increase, the hospital should be in a similar financial position as in previous years, which makes their response indeterminate.	?	?
Bad Debt	↔	A decrease to the increase of MaineCare reimbursement should not affect reported levels of bad debt. There is a small possibility that if the hospitals increased their charges in response to this lower reimbursement, then the level of bad debt could slightly increase. More than likely, though, bad debt should be unaffected.	↔	↔
Hospital Tax	↔	Regardless of whether or not the lower reimbursement level increased the tax amount, the tax is netted out in the calculation of CMAD. There will be no effect.	↔	↔
Inpatient Discharges	↔	A lesser increase in MaineCare reimbursement should not have any effect on the magnitude of inpatient discharges.	↔	↔
Case-Mix Index	↔	A lowered increase in reimbursement should not affect the severity of cases coming into the hospital.	↔	↔
Outpatient Volume Adjustor	↔	The outpatient volume adjustment looks at revenue from both inpatient and outpatient services. Assuming the lowered increase in reimbursement would not affect the mix of services used at the hospital, this ratio would remain unchanged.	↔	↔

Summary
A hospital's response to a decrease in the annual MaineCare reimbursement increase could have many different affects to the calculated cost per CMAD. If the hospital raised their charges or absorbed the lower reimbursement level, then the CMAD would be unaffected. If they lowered their costs to offset the reduction in reimbursement increase, then the calculated CMAD would be lower. Nationally, many states have been subject to decreased Medicaid reimbursement increases, so the fixed-effects of the regression analysis most appropriately control for this issue.

schramm▫raleigh HEALTH STRATEGY
7740 East Gelding, Suite 2
Scottsdale, AZ 85260
480.588.2499 (office)
480.315.1795 (fax)

www.schrammraleigh.com